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# A TEST OF CONSPICUOUS CONSUMPTION: VISIBILITY AND INCOME ELASTICITIES

Ori Heffetz*

*Abstract*—This paper shows that, consistent with a signaling-by-consuming model à la Veblen, income elasticities can be predicted from the visibility of consumer expenditures. We outline a stylized conspicuous consumption model where income elasticity is endogenously predicted to be higher if a good is visible and lower if it is not. We then develop a survey-based measure of expenditure visibility, ranking different expenditures by how noticeable they are to others. Finally, we show that our visibility measure predicts up to one-third of the observed variation in elasticities across consumption categories in U.S. data.

> *Since . . . appearance tyrannizes over truth and is lord of happiness, to appearance I must devote myself.*
>
> Plato, *The Republic*, II

## I. Introduction

THE relationship between total expenditures and expenditure on a certain commodity—the Engel curve—is one of the most fundamental relationships in consumer theory. Yet while empirical estimation of Engel curves is neither uncommon nor new, the reasons for the observed differences in curve shapes are not well understood.[1] Why do household budget shares spent on food at home decrease with income (or total expenditures), while those spent on food at restaurants increase (see figure 3)? What is it that makes one commodity a necessity and another a luxury? Put slightly differently, what can explain the observed cross-expenditure variation in income elasticities?[2]

These questions are rarely asked in economics; economists typically presume that differences in income elasticities merely reflect differences in tastes for different commodities at different income levels.[3] In this paper, we demonstrate that elasticities are to some extent predictable. Specifically, we find that elasticities can be predicted from the sociocultural visibility of consumer expenditures, roughly defined as the speed with which members of society notice a household's expenditures on different commodities.

Our analysis is motivated by an old idea, which we refer to as signaling-by-consuming. Versions of this idea go back at least to Plato, who emphasized the importance of appearance over truth as a guide to happiness. Applied to the behavior of consumers in industrial economies, the observation that visible expenditures may become signals did not escape early writers like Smith and Marx. Later, the idea became the basis of Veblen's (1965) *The Theory of the Leisure Class*, published originally in 1899, where the term *conspicuous consumption* was coined to describe the advertisement of one's income and wealth through lavish spending on visible items. The term has since been continually discussed and applied by economists (see, for example, the conclusions in Spence's 1973 seminal signaling paper). For a brief survey and references to the recent literature on conspicuous consumption, see Heffetz (2004).

This paper thus achieves two goals simultaneously: while explaining some of the observed cross-expenditure variation in elasticities, it provides evidence supporting the idea that households engage in consumption not only for its intrinsic value but also for its value as a signal.

Our argument proceeds in three steps. First, we present a conspicuous consumption model that identifies a mechanism by which visibility determines elasticity. Our next two steps are empirical, and together they constitute the bulk of

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* S. C. Johnson Graduate School of Management, Cornell University.

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[1] On the estimation of Engel curves, see, Blundell and Duncan (1998), whose references date back to Working (1943), and Lewbel (2006), whose review starts a century and a half ago, with Engel's work.

[2] In this paper, we use *income elasticity* and *total expenditure elasticity* interchangeably. In our static model, where no saving or dissaving is possible, the two are indeed identical. In our empirical estimates, we use *total expenditures*.

[3] Hence, economists have effectively been looking to psychology, sociology, and other social sciences for answers. To this day, many answers still come, often implicitly, from variations on Maslow's (1943) famous hierarchy of needs. According to Maslow, individuals first seek to satisfy physiological needs, moving with increasing income to satisfy safety and social needs, through to the higher needs associated with self-actualization.

this paper and its main contribution. In the second step, we construct an empirical measure of expenditure visibility by conducting a survey among U.S. households. Finally, in the last step, we combine results from our visibility survey with elasticity estimates based on Consumer Expenditure Survey (CEX) data and show that the former can indeed predict the latter.

We develop our model in section II. We show that adding a signaling-by-consuming motive to a textbook consumer model can endogenously turn a visible good into a luxury and a nonvisible good into a necessity. To lay bare the mechanism from differences in visibility to differences in elasticity, we intentionally start with a simple two-good model with Cobb-Douglas (CD) utility, where cross-good differences in elasticities do not originate from differences in tastes. Rather, in this model, commodities enter the utility function symmetrically, Engel curves are linear, and elasticities are constant at unity and hence are the same across goods. We then incorporate a signaling motive into the model by using a framework (Ireland, 1994) that adds two elements. First, in addition to their standard utility, consumers also care about others' (or society's) beliefs about this utility. Second, we make the natural assumption that some goods are visible while others are not: in the model, there is one visible good and one nonvisible good. We solve this augmented model and show that in a fully separating equilibrium, consumers tilt increasing budget shares toward the visible good to differentiate themselves from poorer consumers. As a result, the visible good's elasticity endogenously increases, while the nonvisible good's elasticity decreases.

Empirically demonstrating the link between visibility and elasticity requires an empirical measure of visibility. Such a measure is developed in section III, which summarizes the design of and findings from a national survey we conducted among 480 U.S. respondents. By asking respondents how quickly they would notice other households' expenditures on different consumption categories, the survey allowed us to quantify the categories' visibility. We use the survey results to construct a visibility index, which we term *Vindex*. We show that the relative position of different expenditures along the index is fairly stable regardless of index construction method.

In our third and final step, in sections IV and V, we match 29 consumption categories' visibility with 29 elasticity estimates and study the correlations between them. Together, these categories cover virtually all consumer expenditures in the CEX data extracts we use. We nonparametrically estimate elasticities from these data for both the whole population and different demographic groups.

Our main results are presented in section IV. We show that weighted univariate OLS regressions of the elasticities of the 29 consumption categories on their visibility (and a constant term) result in statistically significant and large coefficients and, importantly, high $R^2$'s. In our benchmark whole-population specification, $R^2 = 0.18$, which means that one-sixth to one-fifth of the cross-category variation in elasticities is explained by our visibility measure alone. For the top three income quintiles, $R^2$'s are in the range 0.19 to 0.32, meaning that almost one-fifth to a third of the variation in elasticities is explained by the Vindex (we hardly find any such evidence at the bottom two quintiles).

The robustness of these findings is investigated in section V. We start by dropping single categories out of the regressions. We then move to examine demographic heterogeneity. This is done both by using elasticity estimates from different subsets of CEX households and by using visibility indices based on different subsets of our survey respondents. We show that although demographically based visibility indices differ from each other in interesting ways, they are highly correlated. These high correlations translate to fairly robust results across alternative indices (although some indices do slightly better than others).

We conclude in section VI, where we discuss limitations as well as some of the broader implications of our findings.

Our findings complement those from other studies of visible consumption. An early example is Chao and Schor (1998), who explain brand buying patterns among women's cosmetic products with product visibility. More recently, in independent work, Charles, Hurst, and Roussainov (2009) show that black and Hispanic households devote larger budget shares to visible expenditures than other U.S. households do. They then demonstrate that a simple conspicuous consumption model could predict these differences from observed differences in group income.[4]

## II. Model

This section demonstrates that adding a signaling-by-consuming motive to a textbook consumer model with Cobb-Douglas (CD) utility can endogenously lead to increased income elasticity for a visible good and decreased elasticity for a nonvisible good.[5]

We start with the textbook model. Consumers are identical in all but their exogenous income $y$. They maximize a CD utility function of two goods, $v$ and $w$,

$$f(v, w) = \beta_v \ln(v) + \beta_w \ln(w), \tag{1}$$

under a budget constraint,

$$v + w = y. \tag{2}$$

Defining $\beta \equiv \frac{\beta_v}{\beta_w}$, the standard solution is

$$v = \frac{\beta}{1+\beta} y; \quad w = \frac{1}{1+\beta} y. \tag{3}$$

This model shuts down any mechanism that might explain different elasticities with different tastes across goods. To

[4] Both studies conduct their own visibility surveys. Chao and Schor (1998) conduct an informal survey among twenty female students to rank the social visibility of lipstick, mascara, eyeshadow, and facial cleanser. In an unpublished robustness appendix (available at the *Quarterly Journal of Economics* Web site, http://qie.oxfordjournals.org/), Charles et al. (2009) conduct an online survey among graduate students, which is "very much inspired by" our survey.

[5] See Heffetz (2004) for a fuller treatment, including a more general case, step-by-step derivation of solutions, proofs, graphic illustrations, further discussion, and interpretations.

see this, remember that for the budget constraint to hold, elasticities weighted by their income shares must sum to 1. Hence, elasticities are the same across goods if and only if they are constant at unity. This is equivalent to having linear Engel curves with no intercept (so expenditure shares are constant), as is the case in equation (3).

To add a signaling motive to the model, we embed it in a framework developed by Ireland (1994). The framework adds two elements: the incentive structure and the information structure. Regarding incentives, we add another term to the utility function. In addition to $f(v, w)$, now referred to as fundamental utility, consumers are assumed to care about others' (or society's) beliefs. Specifically—and since everybody has identical preferences—we assume that consumers care about society's beliefs regarding their fundamental utility. In other words, doing well is no longer enough; individuals also want everybody to know (or to mistakenly think) that they are doing well.

Denoting by $\hat{v}$ and $\hat{w}$ society's beliefs regarding $v$ and $w$, the utility function is a convex combination of the two terms—fundamental utility, and society's inferences of it:

$$U = (1-a)f(v, w) + af(\hat{v}, \hat{w}). \quad (0 < a < 1). \tag{4}$$

The weight $a$ can be thought of as a measure of one's sensitivity to society's view or to social status. With $a = 0$, the model reduces to the standard model.

Regarding information, we assume that good $v$ is visible while good $w$ is not—that is, $v$ is observed by others, while $w$ is only privately known. In addition, income $y$ is only privately known, but the lower support of the income distribution, denoted $b$ for bottom income, is common knowledge (this assumption is used to pin down the equilibrium, as discussed below). With this structure, society's inferences about individuals are a function of $v$. Hence,

$$\hat{v} = v; \quad \hat{w} = \hat{w}(v), \tag{5}$$

where $\hat{w}(v)$ is society's beliefs concerning one's unobservable $w$ based on the observable $v$.

One can now solve the model. A fully separating equilibrium requires that (a) individuals' choice of $v$ be optimal given $\hat{w}(\cdot)$, which they take as exogenous, and that (b) society's inferences be correct:

$$\hat{w}(v) = w. \tag{6}$$

One can use equations (2), (4) and (5) to derive a first-order condition for an internal solution to the consumer problem; combine it with equation (6) to find $\hat{w}(v)$, and, for certain choices of $f(\cdot, \cdot)$, complete the solution.

We now depart from Ireland and apply his framework to our CD example.[6] Solving the model with the fundamental utility in equation (1) results in an inverse Engel curve $y(v)$,

$$y = \frac{1+\beta}{a+\beta}v + Cv^{-\frac{\beta}{a}}, \qquad (a > 0), \tag{7}$$

where $C$ is an arbitrary constant (pinned down below). Because equation (7) cannot be written as an explicit Engel curve $v(y)$, it is convenient to compare it with an inverted version of the standard no-signaling solution, equation (3), above:

$$y = \frac{1+\beta}{\beta}v. \qquad (a = 0) \tag{8}$$

To pin down $C$, we use a boundary condition that reflects utility maximization at the lowest income level $b$. In a fully separating equilibrium, deviating from one's no-signaling allocation is suboptimal for the lowest income type. In other words, at $y = b$, both equations (7) and (8) should hold, which pins down $C$ as positive.[7]

Our elasticity-by-visibility result is seen by comparing equations (7) and (8). Whereas in the no-signaling benchmark, equation (8), spending on $v$ is a constant share $\frac{\beta}{1+\beta}$ of $y$, and hence elasticities are constant at unity, social signaling results in an additional nonlinear term on the right-hand side of equation (7). This term, with a positive coefficient, monotonically vanishes as $y$ and $v$ grow, in a way that translates to $v$'s budget share increasing with $y$. As $y$ grows, $v$'s share converges to $\frac{a+\beta}{1+\beta}$ (which, naturally, increases with the status parameter $a$).

Formally, $v$'s elasticity can be calculated from equation (7) and the budget constraint equation (2):

$$e_v \equiv \frac{dv}{dy}\frac{y}{v} = a\left((1+\beta)\frac{v}{y} - \beta\right)^{-1}. \tag{9}$$

Using equation (7), one can show that $e_v > 1$, which, in a two-good model, implies $e_w < 1$ (both asymptote towards unity as $y$ grows). Therefore, compared with the no-signaling elasticities ($e_v = e_w = 1$), introducing social signaling drives $e_v$ up and $e_w$ down. Note that in the CD case, this is equivalent to $v$ becoming a luxury and $w$ a necessity.

The intuition behind this result is as follows. As is common in signaling models with fully separating equilibria, the lowest income type $b$ does not spend on the signal (there is no tilting of the budget toward $v$ at $y = b$). As income rises, in order to differentiate themselves from lower types, individuals have to spend (concavely) increasing shares of their budget on $v$. This drives $v$'s elasticity up (and $w$'s elasticity down).

This highly stylized model captures the intuition that under certain conditions, when $v$ is visible and hence has a signaling benefit in addition to the usual consumption benefit, its elasticity will increase. We know of no general theory making this prediction or any other prediction relating visibility to elasticity. We show in Heffetz (2004) that the framework can be

[6] Ireland (1994) applies his framework to a quasi-linear example, $f(v, w) = v + \log(1 + w)$, which he finds convenient for studying optimal taxation questions. Note that his example assumes significant differences in tastes across the goods, reflected in the different ways in which the goods enter $f(\cdot, \cdot)$.

[7] One can show that the condition above holds only if

$$C = \frac{a}{a+\beta}\left(\frac{\beta}{1+\beta}\right)^{\frac{\beta}{a}} b^{\frac{a+\beta}{a}},$$

which is positive (as long as $a$ and $b$ are positive).

analytically solved for the slightly more general Stone-Geary fundamental utility, which allows elasticities that vary with income and across goods even in the absence of signaling. Our elasticity-by-visibility result carries over to that setup: introducing social signaling leads to an increase in $e_v$ and a decrease in $e_w$.[8]

## III. Measuring Visibility

Moving from model to data requires translating the difference between $v$ and $w$ to an empirical setup. We do this by considering a commodity visible if, in the cultural context in which it is consumed, society has direct means to correctly assess the expenditures involved. If, for example, name dropping the names of schools attended by one's children early in every conversation is a common social practice (and assuming that people rarely lie about such things), then expenditures on school education might be fairly visible.

In other words, the visibility we wish to measure is a sociocultural rather than physical feature of commodities, determined by the sociocultural context in which they are consumed. The prevailing norms, values, customs, beliefs, and laws may all be part of this context, and what is visible in one society at one time and place could be invisible in other societies or in the same society at other times. To measure this notion of visibility, we conducted a U.S. national telephone survey from May 2004 to February 2005. This section describes the survey and its findings.[9]

### A. *Survey Design and Sample*

The main question in our survey read:

> Imagine that you meet a new person who lives in a household similar to yours. Imagine that their household is not different from other similar households, except that they like to, and do, spend more than average on [jewelry and watches].
>
> Would you notice this about them, and if so, for how long would you have to have known them, to notice it? Would you notice it almost immediately upon meeting them for the first time, a short while after, a while after, only a long while after, or never?

Replies to this question were coded 1 (almost immediately) to 5 (never). The question was repeated 31 times for each respondent, with "[jewelry and watches]" in the example above replaced by each of 31 expenditure category titles, randomly ordered. These are listed in table 1. They are based on 47 spending categories created by Harris and Sabelhaus (2005) from the raw CEX data and together cover 99.4% of consumption expenditures in the data we use.[10] The order of words in each category's title listed in table 1 reflects the relative empirical importance (in the CEX data) of the items within that category.

Table 1.—Consumption Categories

| | |
|---|---|
| FdH | Food and nonalcoholic beverages at grocery, specialty, and convenience stores |
| FdO | Dining out at restaurants, drive-throughs, etc, excluding alcohol; including food at school |
| Cig | Tobacco products like cigarettes, cigars, and pipe tobacco |
| AlH | Alcoholic beverages for home use |
| AlO | Alcoholic beverages at restaurants, bars, cafeterias, cafeś, etc. |
| Clo | Clothing and shoes, not including underwear, undergarments, and nightwear |
| Und | Underwear, undergarments, nightwear, and sleeping garments |
| Lry | Laundry and dry cleaning |
| Jwl | Jewelry and watches |
| Brb | Barbershops, beauty parlors, hair dressers, health clubs, etc. |
| Hom | Rent, or mortgage, or purchase, of their housing |
| Htl | Lodging away from home on trips and housing for someone away at school |
| Fur | Home furnishings and household items, like furniture, appliances, tools, and linen |
| Utl | Home utilities such as electricity, gas, and water; garbage collection |
| Tel | Home telephone services, not including mobile phones |
| Cel | Mobile phone services |
| HIn | Homeowner's insurance, fire insurance, and property insurance |
| Med | Medical care, including health insurance, drugs, dentists, doctors, hospitals, etc. |
| Fee | Legal fees, accounting fees, and occupational expenses like tools and licenses |
| LIn | Life insurance, endowment, annuities, and other death benefits insurance |
| Car | The purchase of new and used motor vehicles such as cars, trucks, and vans |
| CMn | Vehicle maintenance, mechanical and electrical repair and replacement |
| Gas | Gasoline and diesel fuel for motor vehicles |
| CIn | Vehicle insurance, like insurance for cars, trucks, and vans |
| Bus | Public transportation, both local and long distance, like buses and trains |
| Air | Airline fares for out-of-town trips |
| Bks | Books, including school books, newspapers and magazines, toys, games, and hobbies |
| Ot1 | Computers, games, TVs, video, audio, musical and sports equipment, tapes, CDs |
| Ot2 | Cable TV, pets and veterinarians, sports, country clubs, movies, and concerts |
| Edu | Education, from nursery to college, like tuition and other school expenses |
| Cha | Contributions to churches or other religious organizations, and other charities |

[8] A technical remark regarding the generalizability of the model: to shut down mechanisms from tastes to elasticities, one has to start with a model where all elasticities are constant at unity. Section II does this with CD utility rather than with the more general CES utility because while Ireland's framework can be analytically solved for the former, it can only be numerically solved for the latter. A model with no closed-form analytical solution is less useful for our purposes in this paper.

[9] See Heffetz (2004) for a detailed description of the survey, its design, and its findings. Here we provide a brief summary.

[10] For a list of Harris and Sabelhaus's (2005) categories, see titles 23–69 at http://www.nber.org/ces_cbo/032/cextitle. For a detailed description of our recategorization method, see Heffetz (2004). For special notes regarding the housing category (`Hom`), see the appendix. Finally, notice that Harris and Sabelhaus do not report expenditures on underclothes and cell phones separately from the much larger categories "Clothing and Shoes" and "Telephone and Telegraph," respectively. Because we took special interest in their visibility, we added to the list in table 1 these two categories: "underwear, undergarments, nightwear and sleeping garments" (`Und`) and "mobile phone services" (`Cel`). The analysis of expenditures and elasticities that follows is based on the other 29 categories.

TABLE 2.—RESPONDENT DEMOGRAPHICS

| | Visibility Survey | | | Census |
|---|---|---|---|---|
| | Observations[a] | Value | (S.E.) | Value |
| Mean values | | | | |
| Age[b] | 467 | 46.6 | (0.7) | 45.2 |
| Household size[c] | 475 | 2.9 | (0.1) | 2.6 |
| Children under 18 in household | 475 | 0.8 | (0.1) | 0.7 |
| Percent distribution | | | | |
| Female | 479 | 64.3 | (2.2) | 50.9 |
| Black | 467 | 13.5 | (1.6) | 12.3 |
| Hispanic | 474 | 6.1 | (1.1) | 12.5 |
| Married[d] | 473 | 55.4 | (2.3) | 54.4 |
| Employed[e] | 473 | 63.2 | (2.2) | 63.4 |
| Education[f] | 474 | | | |
| Elementary (0–8) | | 2.1 | (0.7) | 7.5 |
| High school (9–12) | | 22.2 | (1.9) | 40.7 |
| College (13–16) | | 53.6 | (2.3) | 42.8 |
| Graduate school (17 or more) | | 22.2 | (1.9) | 8.9 |
| Total household income | 388 | | | |
| Less than $20,000 | | 13.4 | (1.7) | 22.1 |
| $20,000 to $40,000 | | 21.1 | (2.1) | 25.3 |
| $40,000 to $60,000 | | 19.3 | (2.0) | 19.7 |
| $60,000 to $100,000 | | 28.1 | (2.3) | 20.6 |
| $100,000 or more | | 18.0 | (2.0) | 12.3 |
| Region | 479 | | | |
| Northeast | | 20.5 | (1.8) | 19.0 |
| Midwest | | 24.0 | (2.0) | 22.9 |
| South | | 39.7 | (2.2) | 35.6 |
| West | | 15.9 | (1.7) | 22.5 |

Sources: Author's visibility survey; Census (2000).
[a] Number of respondents reporting demographic characteristic (out of a total of 480 respondents).
[b] In Census: estimated age of population 18 years and over.
[c] Top-coded at 8 (in visibility survey).
[d] In Census: marital status of population 15 years and over.
[e] In Census: employment status of population 16 years and over (civilian labor force).
[f] In Census: educational attainment of population 25 years and over.

Regarding the wording of the question, remember that in the fully separating equilibrium we focus on, the signal each household sends through its visible consumption $v$ is sufficient for its nonvisible consumption $w$ to be fully worked out by society. With both $v$ and $w$ thus public knowledge, simply asking people how much they know about—or how well they can estimate—different expenditures by other households might not suffice for distinguishing visible from nonvisible consumption. The question above is hence phrased to ask respondents how quickly they would notice an exogenous shock to the tastes of another household; the shock causes that household to deviate, with one expenditure, from the typical equilibrium behavior expected by society. In effect, we identify an expenditure's visibility with the quickness with which such a deviation would be noticed.

We used random digit dialing (RDD) to get a random sample of the population over age 18 in the continental United States. Our response rate is estimated at 15% of working residential numbers (with no language barrier). We completed 480 interviews, with a mean duration of 13 minutes.

Table 2 reports the demographic characteristics of our respondents. The last column reproduces Census (2000) figures. Our sample closely resembles (in first moments) the Census population in age, number of children in the household, and percentage black, married, and employed. Possibly resulting from the telephone methodology, fewer of our respondents are male, Hispanic (language issues), and Western U.S. residents (time zone issues), and they report higher income and education levels (note that one in five refused the income question).

## B. *The Visibility Index*

We first present results based on the full unweighted sample of 480 completed interviews. A discussion of heterogeneity is postponed to section VC, where we show that the visibility index is rather insensitive to the demographic composition of survey respondents.

Table 3 reports three proposed methods of converting our data into visibility indices and rankings. Its first column lists the categories, ordered by the ranking corresponding to the first proposed index. The rest of the columns report, for each of the three proposed indices, index values, standard errors, and the corresponding rankings.

The first proposed index, normalized mean, assigns five equidistant values from 0 to 1 to the five response options and reports, for each category, its mean value over all respondents.[11] The potential range of the resulting index is 0 (least visible) to 1 (most visible). One may object that the index linearizes a scale of responses that is not necessarily linear. In defense, it is simple, it is efficient in using all available information, and, importantly, the resulting ranking is almost identical to the two alternative methods below that do not assume a linear response scale.

These two alternative methods are response 1 or 2, which reports, for each consumption category, the fraction of respondents who replied either "almost immediately" or "a short while after," and response 4 or 5, which reports the difference between unity and the fraction of respondents who replied either "a long while after" or "never." Since these two indices count extreme responses, one could suspect that they measure nothing but the variance of responses for each category if presented alone. However, comparing between columns shows quite clearly that this is not the case. Statistical correlations between indices and rankings across methods range from 0.96 to 0.99.

Overall, table 3 suggests that the surveyed population perceives some expenditures to be substantially more visible than others: all three methods above result in similar indices that cover a substantial segment of the theoretically feasible range [0, 1]. In the rest of this paper we refer as the "visibility scale," "visibility index," or, in short, "Vindex," to the normalized mean index. This choice has no significant effects on our results.

Looking at the findings category by category, the most visible category is, interestingly, tobacco products (`Cig`).[12] While only 13% of respondents said they would take a long while or longer to notice an atypically high expenditure on

[11] The assignment is as follows: 1 = almost immediately; .75 = a short while after; .5 = a while after; .25 = a long while after; and 0 = never.

[12] The fact that expenditures on tobacco products can often be smelled long after the actual act of consumption is over may be counted as yet another kind of visibility.

TABLE 3.—VISIBILITY INDICES AND RANKINGS

| Category | Normalized Mean | | | Response 1 or 2 | | | Response 4 or 5 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Index | (S.E.) | [Rank] | Index | (S.E.) | [Rank] | Index | (S.E.) | [Rank] |
| Cig (cigarettes) | 0.76 | (0.01) | [1] | 0.81 | (0.02) | [1] | 0.87 | (0.02) | [2] |
| Car (cars) | 0.73 | (0.01) | [2] | 0.71 | (0.02) | [3] | 0.89 | (0.01) | [1] |
| Clo (clothing) | 0.71 | (0.01) | [3] | 0.72 | (0.02) | [2] | 0.84 | (0.02) | [5] |
| Fur (furniture) | 0.68 | (0.01) | [4] | 0.66 | (0.02) | [4] | 0.86 | (0.02) | [3] |
| Jwl (jewelry) | 0.67 | (0.02) | [5] | 0.63 | (0.02) | [6] | 0.80 | (0.02) | [7] |
| Ot1 (recreation 1) | 0.66 | (0.01) | [6] | 0.64 | (0.02) | [5] | 0.85 | (0.02) | [4] |
| FdO (food out) | 0.62 | (0.01) | [7] | 0.58 | (0.02) | [7] | 0.82 | (0.02) | [6] |
| AlH (alcohol home) | 0.61 | (0.01) | [8] | 0.57 | (0.02) | [8] | 0.76 | (0.02) | [12] |
| Brb (barbers etc.) | 0.60 | (0.01) | [9] | 0.54 | (0.02) | [9] | 0.77 | (0.02) | [8] |
| AlO (alcohol out) | 0.60 | (0.01) | [10] | 0.52 | (0.02) | [10] | 0.77 | (0.02) | [9] |
| Ot2 (recreation 2) | 0.58 | (0.01) | [11] | 0.51 | (0.02) | [11] | 0.76 | (0.02) | [10] |
| Bks (books etc.) | 0.57 | (0.01) | [12] | 0.48 | (0.02) | [13] | 0.76 | (0.02) | [11] |
| Edu (education) | 0.56 | (0.01) | [13] | 0.49 | (0.02) | [12] | 0.73 | (0.02) | [13] |
| FdH (food home) | 0.51 | (0.01) | [14] | 0.40 | (0.02) | [16] | 0.68 | (0.02) | [14] |
| Hom (rent/home) | 0.50 | (0.02) | [15] | 0.41 | (0.02) | [14] | 0.60 | (0.02) | [16] |
| Cel (cell phone) | 0.47 | (0.02) | [16] | 0.40 | (0.02) | [15] | 0.58 | (0.02) | [18] |
| Air (air travel) | 0.46 | (0.01) | [17] | 0.35 | (0.02) | [17] | 0.62 | (0.02) | [15] |
| Htl (hotels etc.) | 0.46 | (0.01) | [18] | 0.33 | (0.02) | [19] | 0.60 | (0.02) | [17] |
| Bus (public transportation) | 0.45 | (0.02) | [19] | 0.34 | (0.02) | [18] | 0.57 | (0.02) | [19] |
| CMn (car repair) | 0.42 | (0.01) | [20] | 0.29 | (0.02) | [21] | 0.55 | (0.02) | [20] |
| Gas (gasoline) | 0.39 | (0.02) | [21] | 0.31 | (0.02) | [20] | 0.48 | (0.02) | [21] |
| Med (health care) | 0.36 | (0.01) | [22] | 0.23 | (0.02) | [23] | 0.44 | (0.02) | [22] |
| Cha (charities) | 0.34 | (0.01) | [23] | 0.22 | (0.02) | [25] | 0.43 | (0.02) | [23] |
| Lry (laundry) | 0.34 | (0.02) | [24] | 0.24 | (0.02) | [22] | 0.41 | (0.02) | [24] |
| Utl (home utilities) | 0.31 | (0.02) | [25] | 0.23 | (0.02) | [24] | 0.36 | (0.02) | [25] |
| Tel (home phone) | 0.30 | (0.02) | [26] | 0.20 | (0.02) | [26] | 0.36 | (0.02) | [26] |
| Fee (legal fees) | 0.26 | (0.01) | [27] | 0.13 | (0.02) | [28] | 0.29 | (0.02) | [27] |
| CIn (car insurance) | 0.23 | (0.01) | [28] | 0.16 | (0.02) | [27] | 0.25 | (0.02) | [28] |
| HIn (home insurance) | 0.17 | (0.01) | [29] | 0.09 | (0.01) | [29] | 0.17 | (0.02) | [29] |
| LIn (life insurance) | 0.16 | (0.01) | [30] | 0.07 | (0.01) | [31] | 0.16 | (0.02) | [30] |
| Und (underwear) | 0.13 | (0.01) | [31] | 0.07 | (0.01) | [30] | 0.12 | (0.01) | [31] |

Source: Author's visibility survey (480 respondents).

this category, 81% said they would notice it almost immediately or after a short while. Less surprising are the next two most visible categories: cars (`Car`), and clothing excluding undergarments (`Clo`).[13]

The other end of the visibility scale is still less surprising. Atypically large expenditures on undergarments and nightwear (`Und`), as well as on various insurance policies (`LIn` and `HIn`, which include life, home, fire, and property insurance), are thought by at least 83% of respondents to be noticed either after a long while or never. For any of these categories, at most 9% think that they would be noticed almost immediately or after a short while.

Although our survey respondents are quicker to notice the cost of housing (`Hom`) than related expenditures such as utilities (`Utl`), they are still quicker to notice goods inside the house such as furniture and appliances (`Fur`) or computers, audio, video, and musical equipment (`Ot1`). Two possible explanations are either that our respondents talk more about these latter expenditures than about their rent or mortgage (which makes them more visible culturally), or that when visiting a new acquaintance's house, respondents are more aware of the cost of household items than of the cost of the house itself (a more visual aspect of visibility).

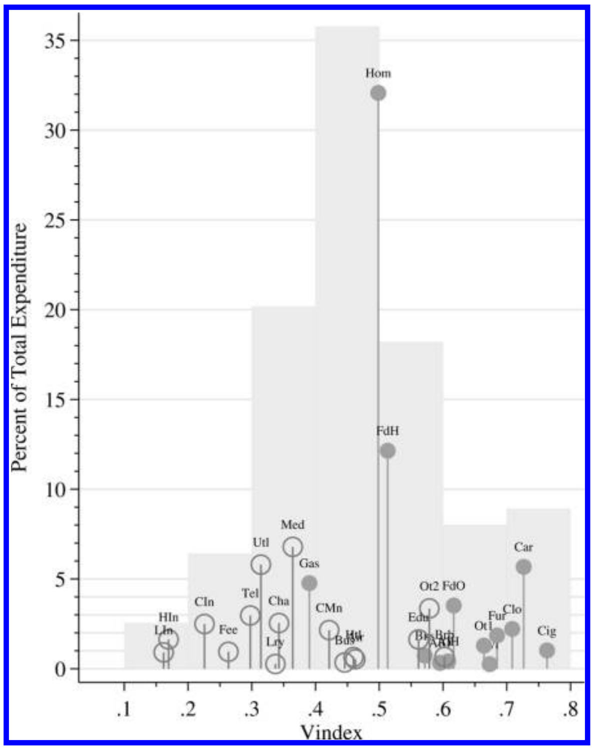
Table 3 reveals an interesting pattern: although its top is unambiguously dominated by durable and nondurable goods, its bottom is dominated by services. At the top of any of the three indices and rankings are goods like cigarettes, cars, clothes, furniture, appliances, jewelry, and equipment (TV, video, audio, musical, and sports). Similarly, with the one exception of underclothes, the bottom is dominated by service-related expenditures like insurance policies, legal and accounting fees, telephone charges, and utilities bills.

This is seen graphically in figure 1. The figure shows the distribution, along the visibility scale, of 29 categories (see note 10) and their expenditure shares. We classify each category as either a good (filled circle) or a service (empty circle).[14] The horizontal axis, Vindex, reproduces the visibility

[13] Respondents' quickness to notice car purchases may be related to recent evidence on social effects in consumption. Grinblatt, Keloharju, and Ikäheimo (2008) find social effects, which occur immediately (within days), of car purchases among Finnish neighbors (notice, however, that they interpret their findings as evidence of information sharing rather than Veblen effects). Kuhn et al. (2008) find social effects of lottery winnings on car consumption and on exterior home renovations in the Netherlands; they invoke high visibility as an explanation. See Frank (1999) for a discussion on cars and visibility.

[14] Although the distinction between goods and services is not unambiguous, with varying classification conventions that are all in constant evolution, most of our categories intuitively belong in one group or the other. The U.S. Bureau of Economic Analysis's (1990, p. 13) conventions, for example, read: "In general, goods are commodities that can be stored, or inventoried. . . . Services are commodities that cannot be stored and that are consumed at the place and time of purchase. If commodities have both a good and service component, the classification generally is based on the relative importance of the two components." We classify the following categories as goods: `FdH, FdO, Cig, AlH, AlO, Clo` (including `Und`), `Jwl, Hom, Fur, Car, Gas, Bks, Ot1`.

FIGURE 1.—CONSUMER EXPENDITURES AND VISIBILITY




Data: $x$-axis: Vindex (second column of table 3), based on author's visibility survey; see table 3 for standard errors. $y$-axis: 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005). Filled circle: a good; empty circle, a service.

index from the second column of table 3.[15] The vertical axis shows how empirically important each category is. The height of each spike corresponds to the average size of the relevant expenditure as a percentage of total household expenditure. It is based on 10,400 households for which full-year expenditure data exist in the 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005).[16] The histogram at the background groups the spikes into seven bars, providing another measure of the empirical distribution of consumer expenditures along the visibility scale.

The sorting pattern that appears in the figure—goods to the right, services to the left—is striking given that our survey question makes neither an explicit nor an implicit distinction between goods and services. While the question asks about spending "more than average on [line from table 1]," the distinction between goods and services seems to emerge from the replies. In other words, a commodity's place on the visibility scale seems highly predictive of the commodity's classification as a good or a service. Below we provide quantitative evidence that a commodity's visibility is highly predictive of its total expenditure elasticity. Here we merely point out, qualitatively, that visibility also seems to predict less formal features of commodities. Although any classification of expenditure categories into goods and services is somewhat arbitrary, the general pattern in figure 1 is visually clear and does not depend on one specific classification.

Figure 1 is otherwise informative in showing that housing (`Hom`) alone accounts on average for almost one-third of expenditures. This, and data issues that are specific to the housing category and are discussed in the appendix, suggest that estimates excluding housing could be viewed as more conservative. We repeated our analysis in the rest of this paper both with and without housing. Encouragingly, our results were not affected more than trivially (see, for example, the discussion in section VA). We therefore kept housing in the reported analysis below.

Finally, figure 1 shows no strong correlation—indeed, at 0.03—between a category's size and its visibility. This rules out the possibility that it is mainly relative size that our Vindex captures. Importantly, the large housing category falls right at the center of the visibility scale. The remaining categories, accounting for two-thirds of total expenditures, are seen to lie around it, with roughly one-third on either side. This helps to explain why housing does not drive our results.

## IV. Visibility and Elasticity: Empirical Analysis

In this section we present our main result: our visibility measure can explain a substantial part of the observed variation in elasticities across consumption categories.

Figure 2 shows nonparametric Engel curve estimates for our 29 consumption categories. The estimates use the same CEX extracts as figure 1. They are obtained using Fan's (1992) locally weighted regression (with quartic kernel) calculated at thirty total annual expenditure points between \$6,863 and \$145,547. This interval stretches from the second to the 99th percentile of the sample of 10,400 households.

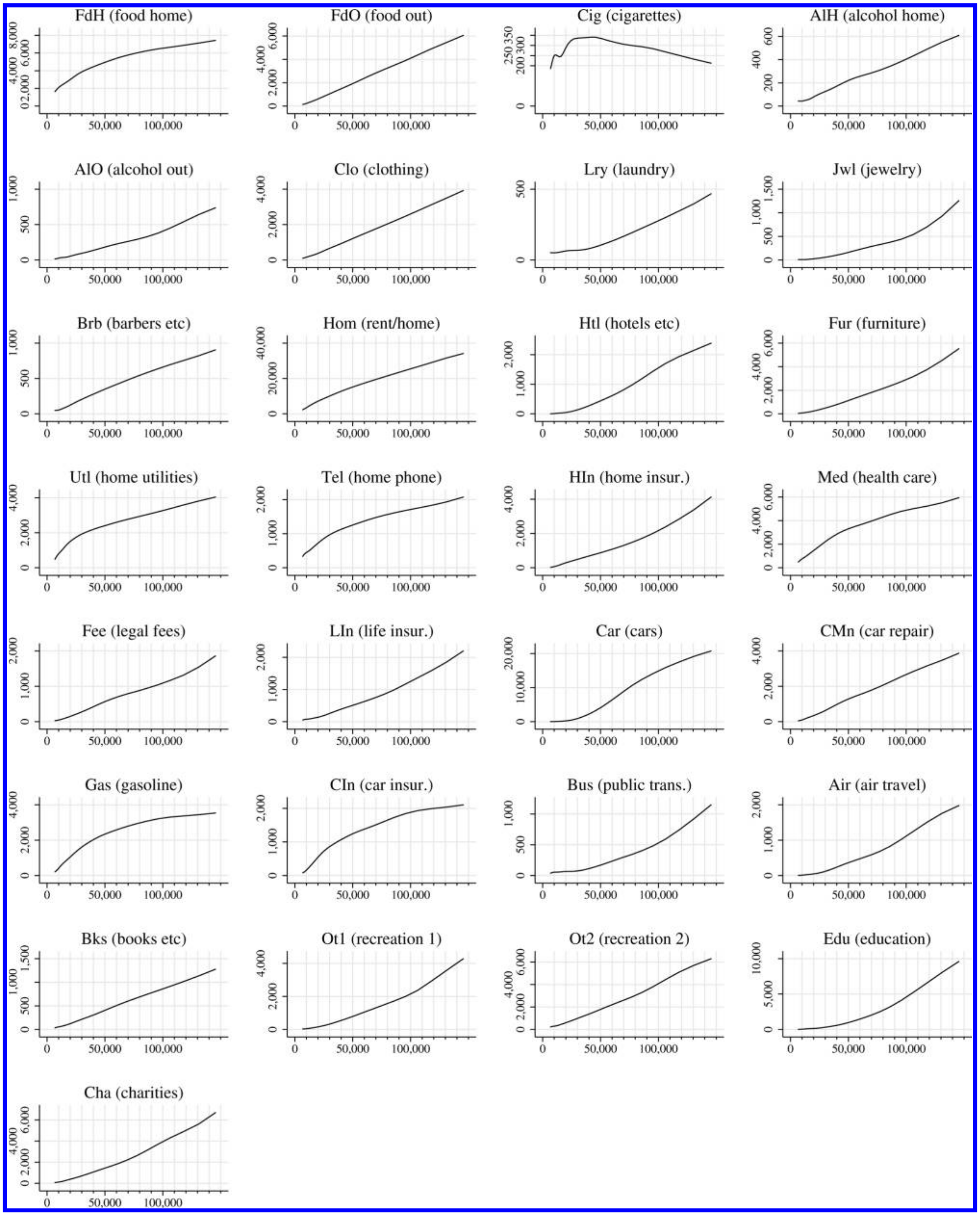
The Engel curves in figure 2 resemble other estimates from the literature in that they exhibit wide cross-commodity variation in their shapes (see Lewbel, 2006, for a review). While some are close to linear, others are highly concave or convex. Still others alternate among linearity, concavity, and convexity at different total expenditure levels. Finally, while most are monotonically increasing, tobacco expenditures (`Cig`)—and, to a much smaller extent, expenditures like public transportation (`Bus`) at low income levels—exhibit intervals of inferior good behavior.

The same data are presented in figure 3 as expenditure shares (reported as a percentage of total expenditure). While luxury goods like cars, education, hotels, and air travel (`Car`, `Edu`, `Htl`, and `Air`) are seen to increase in shares at most income levels, the shares of necessities like food at home, housing, utilities, and telephone (`FdH`, `Hom`, `Utl`, and `Tel`)

[15] Since the horizontal position of the spikes is based on the point estimates (with no indication of confidence intervals), figure 1 should be interpreted only in conjunction with table 3, which reports the relevant standard errors. In practice, however, these standard errors are small.

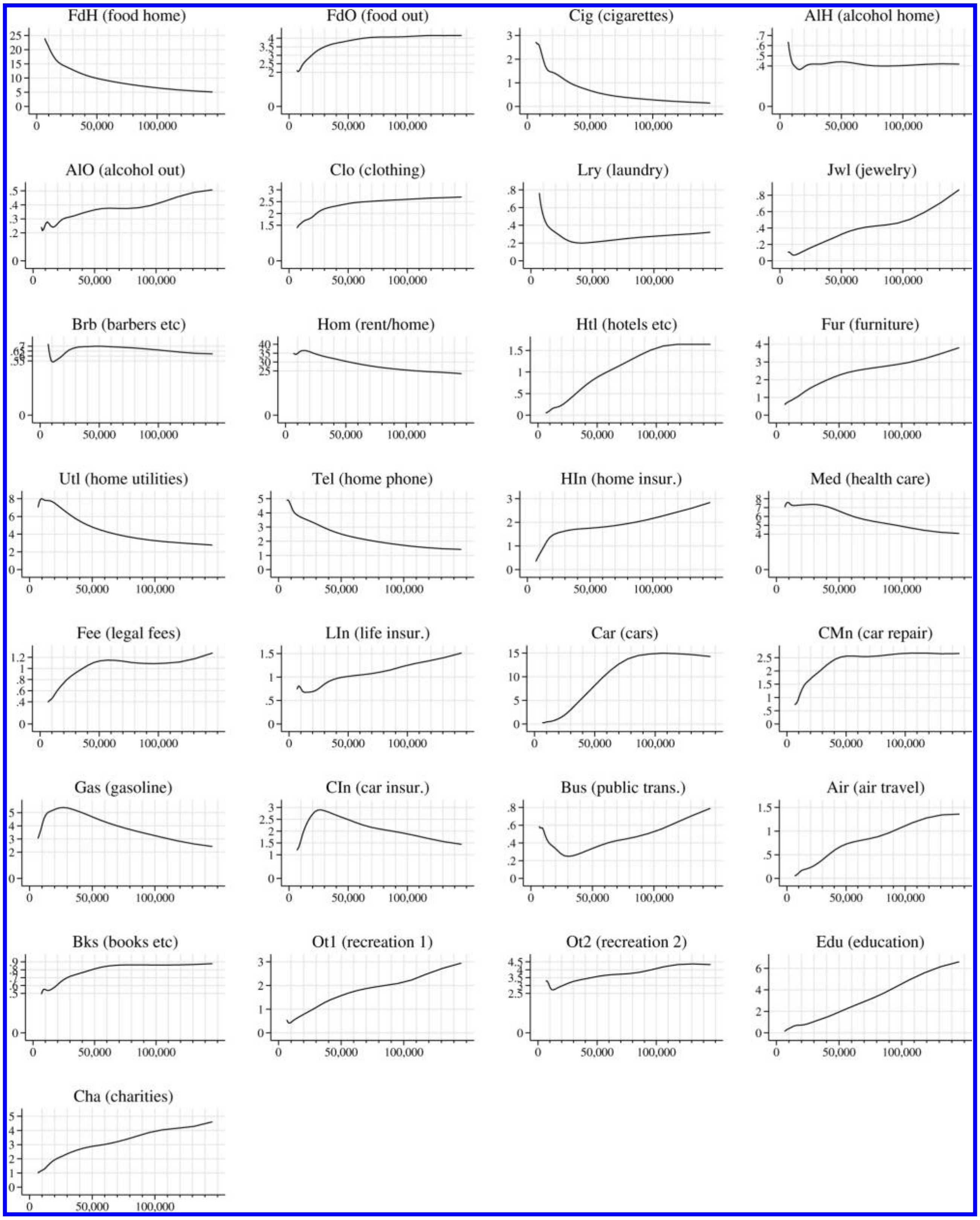
[16] These two sets of CEX data, each consisting of four consecutive quarters, surround the time during which our visibility survey was conducted. Notice that due to the BLS's decennial sample frame rebasing in 2005, households that began the survey in 2004:3 and 2004:4 cannot be tracked for the entire year and hence are not included in our data. We thank Ed Harris for making these data extracts available to us prior to their online availability. Data are converted into real 2005 expenditures using BLS's CPI-U.

FIGURE 2.—ENGEL CURVES: EXPENDITURE LEVELS



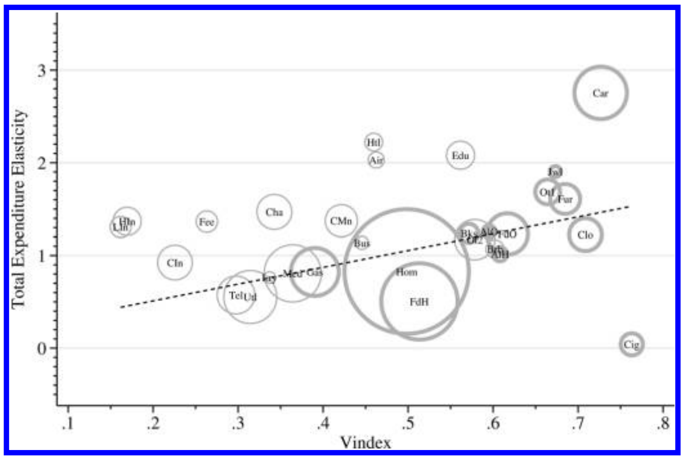

Fan (1992) regressions with quartic kernel (see details in text). Expenditures (both *x*- and *y*-axes) are in US$. Data: 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005).

FIGURE 3.—ENGEL CURVES: EXPENDITURE SHARES




Fan (1992) regressions with quartic kernel (see details in text). Total expenditures ($x$-axis) are in US$. Expenditure shares ($y$-axis) are reported as a percentage of total expenditure. Data: 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005).

FIGURE 4.—VISIBILITY AND ELASTICITY FOR ALL HOUSEHOLDS




Data: *x*-axis: Vindex (second column of table 3), based on author's visibility survey; see table 3 for standard errors. y-axis: average elasticities, estimated nonparametrically using 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005). See details in text. Area of circles is proportional to category size. Dashed line: OLS, weighted by size.

are seen to decrease. Finally, the shares of gas, car insurance (Gas, CIn), and other expenditures alternate between positive and negative slopes: they are luxuries at some income levels and necessities at others.

The regressions that the two figures are based on can be used to construct total expenditure elasticity estimates for each commodity group at each of the thirty total annual expenditure points estimated. We take each locally weighted regression to represent the households that lie in an interval centered at the estimation point and whose length is equal to the distance between two such points. We thus assign a weight to each of the thirty local elasticities, corresponding to the (weighted) number of households in the total expenditure interval they represent. Using these weights, we calculate average elasticity for each consumption category. We do this over the whole population and by five quintiles.[17]

Figure 4 shows the correlation between visibility and elasticity for our 29 consumption categories. The visibility measure on the horizontal axis is our Vindex, as reported in the second column of table 3. The elasticities on the vertical axis are the (whole population) average elasticities described above. Each consumption category is shown as a circle with an area proportional to the size of the category. The rim of the circles is thick for goods and thin for services. The dashed line shows best linear fit, weighted by size.

Figure 4 shows that our empirical measures of visibility and elasticity are indeed positively correlated. The figure is otherwise informative in suggesting which of the consumption categories may or may not fit well into an elasticity-by-visibility story. One example of a good fit is the family of vehicle-related categories. Within this family, visibility and elasticity are strongly positively correlated: while expenditures on the purchase of vehicles (Car) are both highly visible and highly elastic, the related (and complementary) expenditures on vehicle maintenance, gasoline, and insurance (CMn, Gas, and CIn) are both substantially less visible and substantially less elastic. On the other hand, these expenditures on car insurance (CIn), as well as those on homeowner insurance (HIn) and on life insurance (LIn), are seen to have average elasticities that are substantially higher than those of many other expenditures that are significantly more visible. This might result from the fact that insurance schemes are, by their very nature, complementary to other expenditures (against the loss of which they insure).

More generally, insurance schemes resemble many other services in the figure in that at a given visibility level, they have elasticities that are, on average, higher than goods with similar visibility levels. Thus, it appears that at a given visibility level, services are on average more elastic than goods. An alternative (and equivalent) reading of the figure is that at a given elasticity, services appear substantially less visible than goods. Below we quantify these differences in a regression setup. As to interpretations, an intuitive one would be that our visible versus nonvisible consumption allocation model could apply to allocations within expenditures on goods separately from allocations within expenditures on services.

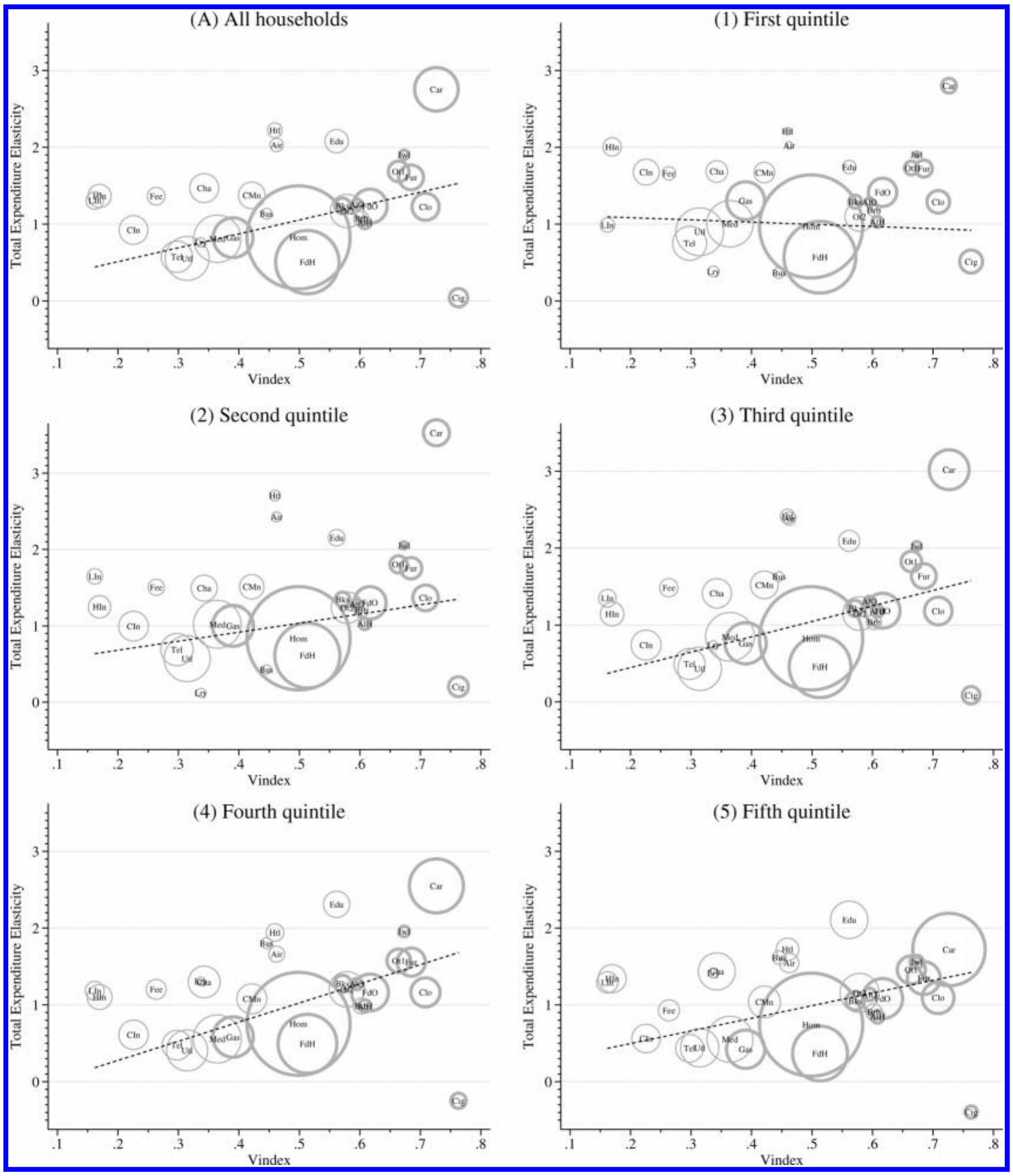
Finally, expenditures on cigarettes (Cig), at the bottom-right corner, seem to fit our model perversely. This suggests that our simple signaling model does not capture well the intricate social and cultural aspects of the behavior of U.S. smokers.[18]

Next, figure 5 reproduces a minimized version of figure 4 (in its top-left corner), as well as five additional versions that correspond to five total expenditure quintiles. These versions are instructive in that they again illustrate graphically the fact that elasticities may be far from constant. Furthermore, the range within which the elasticity of each commodity varies exhibits substantial variation across commodities. Compare, for example, expenditures on contributions and charities (Cha) with those on laundry and dry cleaning (Lry), both at a visibility level of 0.34 (see table 3). While the former retains income elasticity above unity (and never too far above it) at all income levels, the latter changes from being, on average, close to inelastic at lower incomes (second quintile), to having elasticity well above unity at higher incomes (fifth quintile).

[17] Due to the discreteness of the locally weighted regression grid, each quintile represents 20% ± 3% of the weighted household population.

[18] Remember that our model assumes away the negative externalities inflicted on society by smokers. It could be argued that today, most smokers in the United States prefer others not to notice that they smoke. Accordingly, while smoking an expensive brand is likely to be perceived as more prestigious than smoking a cheap brand, forgoing this expenditure altogether (by not smoking) might be perceived as more prestigious than both. This could be seen as an instance of Congleton's (1989, p. 176) "institutional arrangements . . . which promote games generating positive externalities and discourage those which do not," and explain the finding that in spite of being the most visible expenditure in our data, smoking is not used by high-income households to advertise their welfare. An alternative explanation is that smoking is currently viewed as a signal of having a self-control problem.

FIGURE 5.—VISIBILITY AND ELASTICITY FOR ALL HOUSEHOLDS AND BY QUINTILES




Data: *x*-axis: Vindex (second column of table 3), based on author's visibility survey; see table 3 for standard errors. *y*-axis: average elasticities, estimated nonparametrically using 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005). See details in text. Within each graph, area of circles is proportional to category size. Across graphs, `Hom` category circle is normalized to an equal size. Dashed lines: OLS, weighted by size.

These cross-quintile variations in elasticities, along with the related variations in the relative weight of each expenditure, translate to a substantial cross-quintile variation in the correlation between visibility and elasticity. As seen by the changing slope of the dashed line along quintiles in figure 5, the overall correlation seen at the top left is driven by strong correlations at the top three quintiles.

We now turn to examine the weighted OLS regressions depicted by these dashed lines. These are reported in table 4 in six columns that correspond to the six graphs in figure 5. In interpreting these regressions, one should bear in mind that because they are based on only 29 observations, results may depend crucially on each expenditure. We will return to this point when discussing robustness checks.

Panel A reports results from the regressions depicted by the dashed lines in the figure. The left-most column, column (A), corresponds to graph A. It shows that overall—for the whole population of households and all consumption categories—the positive correlation between visibility and elasticity is significant economically and statistically. The Vindex coefficient is large and significant ($p = 0.02$), and the $R^2$ shows that our visibility survey predicts a substantial 18% of the

TABLE 4.—ELASTICITY AND VISIBILITY

| | (A) All Households | (1) First Quintile | (2) Second Quintile | (3) Third Quintile | (4) Fourth Quintile | (5) Fifth Quintile |
|---|---|---|---|---|---|---|
| | | | A. No Controls | | | |
| Vindex | 1.81** | −0.29 | 1.18 | 2.00** | 2.49*** | 1.64*** |
| | (0.74) | (0.61) | (0.77) | (0.79) | (0.70) | (0.57) |
| $R^2$ | 0.18 | 0.01 | 0.08 | 0.19 | 0.32 | 0.23 |
| | | | B. Service or Good Control Included | | | |
| Vindex | 3.20*** | 0.38 | 2.54** | 3.49*** | 3.90*** | 3.00*** |
| | (0.88) | (0.82) | (0.96) | (0.95) | (0.81) | (0.61) |
| Service | 0.61** | 0.24 | 0.54** | 0.64** | 0.65** | 0.67*** |
| | (0.24) | (0.20) | (0.25) | (0.26) | (0.24) | (0.19) |
| $R^2$ | 0.34 | 0.06 | 0.22 | 0.34 | 0.47 | 0.49 |
| | | | C. Service or Good and Vindex × Service or Good Controls Included | | | |
| Vindex | 4.61*** | 0.97 | 3.69** | 4.92*** | 5.24*** | 3.83*** |
| | (1.13) | (1.15) | (1.33) | (1.24) | (1.02) | (0.79) |
| Service | 2.01** | 0.77 | 1.58* | 2.03** | 2.03** | 1.56** |
| | (0.78) | (0.74) | (0.87) | (0.85) | (0.73) | (0.59) |
| Vindex × Service | −3.15* | −1.21 | −2.38 | −3.15* | −3.07* | −1.91 |
| | (1.69) | (1.65) | (1.91) | (1.83) | (1.55) | (1.19) |
| $R^2$ | 0.42 | 0.08 | 0.26 | 0.41 | 0.54 | 0.54 |

All regressions are OLS with 29 observations, weighted by size of consumption category. Dependent variable: average total expenditure elasticity (see estimation procedure and details in text), using 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005). Main regressor: Vindex (second column of table 3), based on author's visibility survey; see table 3 for standard errors. All regressions include a constant (not reported). Standard errors in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

cross-commodity variation in elasticities. Columns 1 to 5 put figures on the changing slope of the dashed lines. Although no visibility-elasticity correlation is found at the bottom two quintiles, it is substantial at the top three, with $p < 0.01$ and $R^2$'s in the range 0.23 to 0.32 for the fourth and fifth quintiles.

Panel B repeats the regressions from panel A, with an added control indicating whether each commodity is a good (service $=$ 0) or a service (service $=$ 1). The reported results again verify what is seen graphically in figure 5: controlling for visibility, the elasticities of services are substantially higher than those of goods (the average difference over the whole population is above 0.6 of a unit elasticity, with $p < 0.05$ for the whole population and for each quintile but the bottom one). Correspondingly, the addition of the service dummy drives up both the size and the significance of the Vindex coefficient. The fit of this augmented model improves substantially, and over one-third of the variation in elasticities is explained between the Vindex and the service dummy ($R^2 = 0.34$ in column A). Model fit is seen to improve with income until it peaks at the fifth quintile, with $R^2 = 0.49$.

As a single regressor, the service dummy has no explanatory power: in regressions (not reported) that repeat the specifications from panel B without the Vindex variable, both the service coefficient and $R^2$ are virtually 0. In other words, while information regarding whether we classify a commodity as a good or a service is in itself uninformative regarding elasticity, the same information becomes a strong predictor of elasticity when coupled with information on the commodity's visibility. The findings in panel B are thus consistent with a model where individuals allocate resources between visibles and nonvisibles separately for goods and for services.

To further explore this idea, panel C adds an interaction of Vindex × Service to the regressions. $R^2$'s are seen to increase, and the interaction coefficient is moderately statistically significant, with $p$-values in the range 0.06 to 0.12 for the whole population and for each of the top three quintiles. While one should beware of overinterpreting this specification, the consistently negative interaction coefficient may suggest that the visibility-elasticity correlation is higher among goods than among services. Under this interpretation, while among goods the correlation is high and significant in all quintiles but the bottom one, among services, it remains positive but it is statistically distinguishable from 0 only in the top two quintiles.

## V. Robustness

To examine the robustness of our main findings, in this section we estimate alternative specifications of the regressions from table 4. We start, in section VA, by leaving out different expenditure categories. We then move to investigate demographic heterogeneity in both the CEX data and our visibility survey responses. In section VB, we replace the elasticity estimates in the regressions with estimates based on demographic subgroups of the CEX population. Finally, in section VC, we also replace the visibility index with indices that are based on demographic subgroups of our survey respondents.

### A. *Expenditure Categories*

In order to examine how our findings depend on each expenditure, we subjected the regressions in table 4 to "influential analysis" (Hayashi, 2000). We repeated each of the 18 regressions 29 times, each time leaving a single expenditure category out of the regression. The resulting 522 regressions

TABLE 5.—ELASTICITY AND VISIBILITY BY DEMOGRAPHICS (10th–95th PERCENTILES)

| | (A) All | (1) Age < 50 | (2) Age ≥ 50 | (3) Married | (4) Nonmarried | (5) Black | (6) Nonblack |
|---|---|---|---|---|---|---|---|
| | | | | A. No Controls | | | |
| Vindex | 2.03** | 1.83** | 2.07** | 2.45*** | 2.05** | 1.97* | 2.00** |
| | (0.76) | (0.76) | (0.80) | (0.83) | (0.80) | (0.98) | (0.74) |
| $R^2$ | 0.21 | 0.18 | 0.20 | 0.25 | 0.20 | 0.13 | 0.21 |
| | | | | B. Service or Good Control Included | | | |
| Vindex | 3.47*** | 3.12*** | 3.72*** | 4.09*** | 3.44*** | 3.69*** | 3.41*** |
| | (0.90) | (0.89) | (0.98) | (0.97) | (0.97) | (1.23) | (0.88) |
| Service | 0.63** | 0.61** | 0.67** | 0.72** | 0.59** | 0.72** | 0.62** |
| | (0.25) | (0.26) | (0.26) | (0.27) | (0.27) | (0.34) | (0.25) |
| $R^2$ | 0.36 | 0.32 | 0.36 | 0.41 | 0.32 | 0.26 | 0.37 |
| | | | | C. Service or Good and Vindex × Service or Good Controls Included | | | |
| Vindex | 5.02*** | 4.47*** | 5.56*** | 5.58*** | 5.23*** | 5.93*** | 4.90*** |
| | (1.15) | (1.12) | (1.26) | (1.24) | (1.23) | (1.56) | (1.11) |
| Service | 2.16** | 2.02** | 2.41*** | 2.22** | 2.34** | 2.88** | 2.10** |
| | (0.79) | (0.80) | (0.85) | (0.87) | (0.85) | (1.06) | (0.77) |
| Vindex × Service | −3.47* | −3.15* | −3.95** | −3.39* | −3.96** | −4.94** | −3.35* |
| | (1.71) | (1.71) | (1.84) | (1.87) | (1.83) | (2.32) | (1.67) |
| $R^2$ | 0.45 | 0.40 | 0.46 | 0.48 | 0.43 | 0.37 | 0.46 |

All regressions are OLS with 29 observations, weighted by size of consumption category. Dependent variable: average total expenditure elasticity for the 10th–95th total expenditure percentiles (see estimation procedure and details in text), using 2003:3–2004:2 and 2005:1–2005:4 CEX extracts from Harris and Sabelhaus (2005). Main regressor: Vindex (second column of table 3), based on author's visibility survey; see table 3 for standard errors. All regressions include a constant (not reported). Standard errors in parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

(not reported), each with 28 observations, allowed us to examine how results are affected by the inclusion or omission of each category. In other words, this part of the analysis offered a systematic way to examine and quantify—expenditure by expenditure and quintile by quintile—which commodities fit our elasticity-by-visibility narrative and which do not. We provide a brief summary of the findings.

As suggested by figures 4 and 5 and as already discussed, the most important expenditure that fits our elasticity-by-visibility model is that on cars. Without the `Car` category, the Vindex coefficient invariably drops, rendering panel A results insignificant. Panel B results remain economically and statistically significant. For the overall population (column, A, panel B), $R^2$ drops from 0.34 to 0.22 (and the $p$-value of the Vindex coefficient increases from 0.001 to 0.03). For the third, fourth, and fifth quintiles (columns 3, 4, and 5, panel B), $R^2$'s drop to 0.23, 0.32, and 0.37, respectively, and $p$'s increase to 0.02, 0.003, and 0.004. This suggests that while cars play a significant role in the visibility-elasticity correlation, an interesting finding in itself, a strong correlation remains among the other 28 expenditures once a good or service control is included.[19] Finally, leaving out any expenditure category other than `Car` does not weaken the correlation more than trivially.

On the other hand, as suggested by the graphs and the previous discussion, some expenditures do not fit our narrative well. Most notably, leaving expenditures on tobacco (`Cig`) out of the regressions substantially improves the fit in all specifications: $R^2$'s in columns A, 3, 4, and 5 increase to 0.23 to 0.37 in panel A, to 0.41 to 0.54 in panel B, and to 0.52 to 0.64 in panel C. Other categories, when left out, increase $R^2$'s in some of the regressions, although less consistently.

[19] In panel C, without the `Car` category, $R^2$'s for the third, fourth, and fifth quintiles drop to 0.23, 0.32, and 0.38, and $p$'s increase to 0.1, 0.04, and 0.03.

### B. *CEX Heterogeneity and Elasticities*

We reestimated Engel curves and elasticities, employing the methods above but replacing the full set of 10,400 CEX households with subsets that were based on household head demographics. We focused on age, marital status, and race. These demographics mattered the most in our visibility survey (see below). We reestimated elasticities six times for six groups (by household head): (1) age below 50 (4,931 households, or 47.4% of all households); (2) age 50 or above (5,469 households); (3) married (6,036 households, or 58.0%); (4) nonmarried (4,364 households); (5) black (1,111 households, or 10.7%); and (6) nonblack (9,289 households).

Based on the six sets of elasticities, we reestimated, six times, regressions similar to the "All Households" column in table 4. But instead of averaging elasticities over the range of total expenditures between the 2nd and the 99th percentiles of the 10,400 households, we averaged elasticities over a narrower range: from the 10th to the 95th percentiles (of the 10,400 households). This guaranteed that elasticities for each demographic group were not estimated outside the range of 2nd to 99th total expenditure percentile for that group.[20] We used the same (all population) Vindex.

Results are presented in table 5. Column A reproduces column A from table 4 for the narrower range of total expenditures. It reports estimates that are, as expected, close to those in the same column in table 4. The rest of the columns, report estimates for each of the six (demographically based) elasticity sets.

[20] As expected, there is no perfect overlap in the range of total expenditures among the six demographic groups (for example, total expenditures are significantly lower, on average, among black than among nonblack households, or among nonmarried than among married ones). For results to be comparable across demographic groups, total expenditure cutoffs should remain constant across groups.

Table 5 reveals a remarkable similarity across its columns in each of the three panels. Most coefficients remain close in size, and most $R^2$'s remain within a comparable range. Interestingly, the "Married" column is at the high end of the range in both Vindex coefficients and $R^2$'s. At the other end of the range, the $R^2$'s in the "Black" column are somewhat lower than the rest, although the Vindex coefficients are not.

To test whether the coefficients are equal across demographic groups, we stacked the data on which the different columns of table 5 are based, added demographic group indicators and interactions, and estimated all the columns of the table together in one regression for each of the three panels (not reported). We allowed clustering of standard errors by consumption category and varied which group indicator/interaction terms are included in the regressions. This allowed us to test for equality of the Vindex coefficient across the two complementary groups in each of the demographic pairs (age, marital status, and race) under different assumptions.[21]

We found that across all specifications, the only demographic pair where cross-group equality of the Vindex coefficient can be rejected is that based on marital status. In panel A, equality of the constant term between married and nonmarried households is rejected ($p = 0.05$), and when the constant term is allowed to differ, but not when it is not, equality of the Vindex coefficient is rejected as well ($p = 0.03$). This finding carries to panel B, where equality of both the constant and the Vindex coefficients between married and nonmarried households can be rejected ($p = 0.06$ and $p = 0.05$, respectively, when the good or service indicator is kept constant across groups; $p = 0.04$ and $p = 0.04$ when the good or service indicator is allowed to differ). In panel C, the equality of neither the constant nor the Vindex coefficient can be rejected.

We conclude that the finding that our visibility measure is a strong predictor of elasticity carries over from whole-population elasticities (column A) to elasticities estimated from households that belong to smaller demographic groups (columns 1–6). While the visibility-elasticity association in our benchmark specification is found to be stronger among married than among nonmarried households, it does not seem to differ significantly along age or race. To the extent that our findings are interpreted as evidence of conspicuous consumption behavior, and hence, of a taste for status ($a > 0$ in our model), we find little evidence that such behavior characterizes only certain demographic groups.

### C. *Heterogeneity in Visibility*

To probe the sensitivity of our findings to the demographic composition of our survey respondents, we proceed in three steps. First, we examine the sensitivity of our visibility index to the underlying population of respondents and construct demographically based indices. Second, we use the indices to reestimate the regressions in column A of table 5. Finally, to look at possible interactions between demographic heterogeneity in CEX data and in our visibility survey, we use the indices to reestimate the regressions in columns 1 to 6 of table 5.

*Demographically based visibility indices.* How sensitive is our visibility measure to the demographic composition of survey respondents? The answer depends on what aspect of visibility one is interested in and could be summarized as follows. The exact visibility level of some expenditure categories could crucially depend on the underlying population of respondents. At the same time, the entire index and the overall visibility ranking, or ordering, of the categories relative to each other are rather stable across demographic groups. We highlight a few examples and discuss implications.

In regressions of visibility responses on the demographic variables reported in table 2, the most significant coefficients are often those on age, marital status, race, and income.[22] Focusing on these demographics, figure 6 illustrates this graphically. In each of its four graphs, three visibility indices are charted along the horizontal axis. The first, marked with black Xs, is the Vindex (second column of table 3), which is based on the full sample of 480 respondents. The other two—dark gray diamonds and light gray triangles, accompanied by their respective 95% confidence intervals—are based on two complementary subsets of the full sample, divided along one demographic characteristic. The four division criteria are above and below 50 years of age, married and nonmarried, black and nonblack, and above and below median income. To facilitate comparison across graphs, the categories are sorted along the vertical axis by their Vindex rank (fourth column of table 3).

Figure 6 reveals interesting findings. For example, on the age graph, the visibility of clothes (`Clo`) is significantly higher when the index is based on younger than on older respondents. Even more so, on the race graph, the visibility of expenditures on barbershops, beauty parlors, hairdressers and health clubs (`Brb`), home telephone services (`Tel`), charity (`Cha`), and many other categories is strikingly higher when the index is based on black rather than on nonblack respondents.

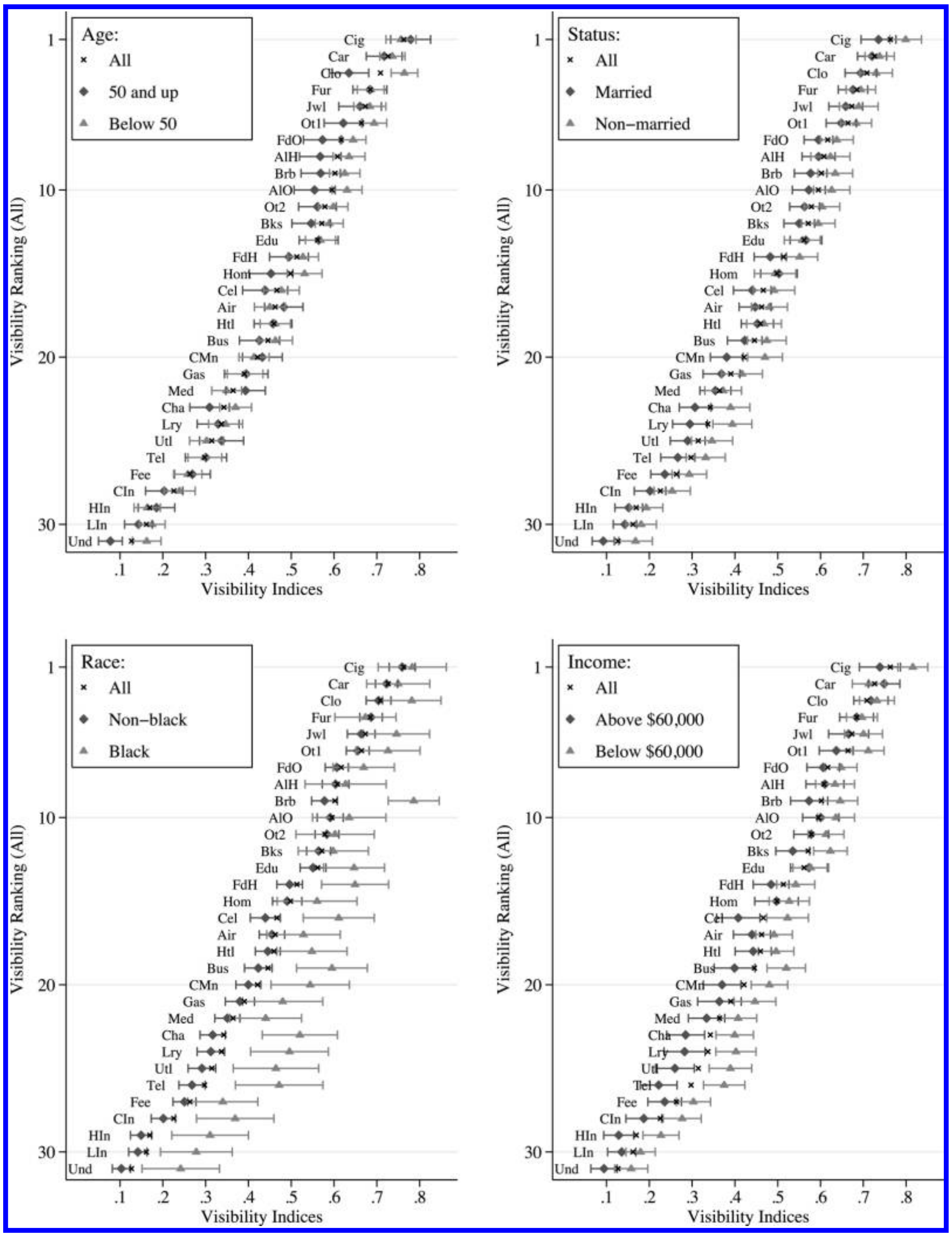
These findings should be interpreted with caution, bearing a few points in mind. First, correlations in demographics render the four demographic divisions far from orthogonal. For example, black and nonmarried households are, on average, also of lower income. One should therefore refer to visibility outcomes among underlying populations rather than attempt to infer a causal link originating from a demographic characteristic.

Second, since respondents are asked only about households similar to theirs, respondents from each demographic

[21] In each panel, we tested whether the constant term should be allowed to differ across groups and whether the Vindex coefficient is equal across groups when the constant term is or is not allowed to differ. In panel B we additionally studied two specifications, where the good/service control is and is not allowed to differ across groups. Naturally, specifications where the constant term and, when applicable, the good/service control are allowed to differ across groups result in estimated coefficients identical to those in table 5.

[22] In Heffetz (2007) we report and discuss the results of several hundred regressions of this type. The discussion here is informed by and summarizes the main findings from these regressions.

FIGURE 6.—VISIBILITY BY RESPONDENT DEMOGRAPHICS




Source: author's visibility survey (480 respondents). Confidence intervals are 95%.

group are in effect asked about the visibility of expenditures in their demographic group only. As a result, cross-group differences in the perceptions of the signal-receiving side—the respondent—are not identified separately from cross-group differences in the behavior of the signal-sending side—the other similar households.[23]

[23] For example, if younger respondents report higher visibility levels, this could imply that the young tend to notice expenditures more quickly than the old do, that young households make their expenditures more noticeable than older households do, or both.

Third, as in any other survey, the responses in our data may or may not reflect respondents' true thoughts, which in turn may or may not reflect reality. In other words, respondents' replies could be affected by the way they perceive the questions, perceive themselves, would like to perceive themselves, or would like to be perceived by their interviewer. Some demographic groups may be more likely to systematically shift their responses in any direction and for any reason. For example, different groups might have different understandings or interpretations of the reply scale.

We return to these points below. Importantly, however, while figure 6 indeed shows that the visibility index values of some expenditures depend crucially on the demographic composition of the underlying sample, it also shows that the visibility of most expenditures relative to each other remains largely similar across demographic groups. This can be seen in all four graphs. For example, in the race and income graphs, many triangles (and their confidence intervals) are visually removed to the right from the corresponding diamonds, especially toward the bottom. However, the relative horizontal order of the triangles is often seen quite similar to that of the diamonds. Indeed the statistical correlation between any two of the nine indices or, alternatively, any two of the nine rankings in the figure is in the range 0.94 to 1.00.

*Visibility indices as regressors*. We reestimated the regressions in column A of table 5 eight times, replacing the Vindex regressor with each of the eight demographically based indices from figure 6. These eight alternative versions (not reported) showed limited variation. The Vindex coefficient remained in the range 1.78 to 2.38 in panel A, 3.24 to 3.50 in panel B, and 4.52 to 5.21 in panel C.

Since the high correlations between the demographically based visibility indices meant that horse-race regressions that included more than one index at a time were impractical (and indeed provided meaningless results), we instead tested for equality of coefficients across the separate regressions. This was done by a method identical to that described in section VB: stacking the data on which column A and its eight alternative versions are based, adding demographic group indicators and interactions and estimating all nine regressions together (separately for each of the three panels). Our results could be summarized as follows. First, in none of the three panels could we reject equality of either the Vindex coefficient or the constant term within any complementary pair of demographically based index regressions (for example, married versus nonmarried). And second, when the constant term was not allowed to differ across regressions, the Vindex coefficient was consistently higher in regressions that use visibility indices based on only higher-income, nonblack, or older respondents (compared with the complementary groups).[24] The respective $p$-values from equality-of-coefficients tests were 0.14, 0.08, and 0.05 in panel A and slightly lower in panel B (0.05–0.09, 0.02–0.03, and 0.00–0.01, depending on whether the good/service control was allowed to differ) and in panel C.

To explore these results further and attempt to interpret them, we estimated another set of regressions where both the dependent variable (elasticities) and the regressor (visibility index) were based on different demographic groups. These regressions are described next.

[24] An index based on the 63 black respondents in our sample is noisier (see figure 6) and hence is expected, by construction, to be a worse predictor of elasticities. By the same token, the nonblack index is virtually identical to the whole-population Vindex.

*Interactions*. Applying the procedures above, we reestimated eight versions (not reported) of each of the rest of the columns of table 5 based on the eight different visibility indices. This allowed us to explore possible interactions between heterogeneity in CEX households and heterogeneity in visibility survey respondents. When we stacked the regressions, the results for each of columns 1 to 6 of table 5 were similar to the results for column A: in none of the columns (and none of the panels) could we reject the equality of either the Vindex coefficient or the constant term within any complementary pair of demographically based-index regressions, and when the constant term was not allowed to differ across regressions, the Vindex coefficient was consistently and significantly higher in regressions that use visibility indices based on only higher income, nonblack, or older respondents (compared with the alternatives). This latter result held rather uniformly across columns: visibility indices with higher or lower coefficients remained so regardless of the demographic group used for elasticity estimates. Moreover, $p$-values were close to those reported for column A, under the *visibility indices as regressors* header above with one exception: those corresponding to column 5 were higher and less significant (they ranged from 0.02 to 0.25).

In summary, our reading of this part of the analysis is as follows. We find no evidence that the elasticities of one demographic group are best predicted by a visibility measure based on respondents from that same group. Rather, we find that a visibility measure based on a fairly representative sample of the population, our Vindex, remains a good predictor of elasticities, whether these are estimated from the whole population or from smaller groups. These predictions may be improved on by an index based on only older, nonblack, or higher-income respondents. Whether this may suggest targeted signaling or merely more reliable respondents is left for future research.

## VI. Conclusion

Our finding that a visibility measure based on a simple survey question predicts up to one-third of cross-good heterogeneity in income elasticities provides evidence consistent with a strong conspicuous consumption motivation in economic behavior. Methodologically, we view our contribution in the tradition of an extended Stigler-Becker (1977, p. 89) view, according to which theories explaining economic behavior should rely on measurable variables rather than on "ad hoc assumptions concerning tastes." Our analysis demonstrates that differences in elasticities can be predicted from differences in a measurable feature of expenditures—their visibility.

We view our evidence as only a first step, for several reasons. First, we show only correlations. One could imagine a mechanism through which high-elasticity expenditures become more socioculturally visible—for example, because the population is interested in what the rich consume or because producers, or even the government, have incentives to make luxuries visible. Our analysis does not test between our mechanism and such reverse-causality alternatives.

Second, the fact that strong correlations between visibility and elasticity are found in our data only at the top quintiles may be interpreted in several ways. One interpretation suggests that the social effects that underlie the correlations are economically significant only at higher (either absolute, or relative) income levels.[25] An alternative interpretation is that to uncover these effects in lower quintiles, one may need to study social groups that are smaller than the broad demographic groups we study.

Finally, our evidence is limited to one country, at one point in time, with consumer expenditures divided into only 29 categories. Replication with variations along these dimensions would help to probe the generalizability of our findings.

With these caveats, our finding of a visibility-elasticity correlation may have broad implications on economic phenomena beyond social signaling. An example from microeconomics is social learning theories, where individuals base their actions on what they learn observing others—possibly to the point of ignoring their own private information (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). A central assumption in these models is that while actions (like spending or consumption) are observable, the information they are based on is not (or not credibly). Our finding that larger budget shares are visible at higher incomes implies that fads, fashions, and herd behavior should be more important at higher incomes.

A closely related example from macroeconomics concerns the speed with which an asset crisis may translate into a recession. A negative income or wealth shock that first affects higher-income households and is translated into consumption cutbacks at the top is predicted, according to our findings, to disproportionately affect visible expenditures. This makes the cutbacks quickly noticeable by other households, potentially causing them to quickly update beliefs and expectations and cut their own consumption. On the other hand, a recovery that starts at the top is predicted to have a similar effect in the opposite direction (namely, an accelerated recovery).

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[25] Interestingly, this interpretation did not necessarily seem intuitive to Veblen. Although focusing on the leisure class, he wrote of "pretence of pecuniary decency" through conspicuous consumption as a "need," common to to all classes of humanity: "There is no class and no country that has yielded so abjectly before the pressure of physical want as to deny themselves all gratification of this higher or spiritual need" (Veblen, 1965, pp. 85–86).


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## APPENDIX

### Expenditures on Housing

Housing is by far the most empirically important expenditure category and deserves special care. While the expenditure on rented housing is a relatively straightforward and easily understood category that reports a monthly payment, calculating the equivalent monthly expenditure on owned housing is more subtle. Our approach, following Harris and Sabelhaus (2005) and others, is to adjust the category "Rental Equivalence of Owned Home" (title 75 in their data) to be comparable to the costs attached to rented housing and add them all together in one category.

While this approach bypasses a few data problems, some issues remain. Among these are the fact that rental equivalence is a proxy and hence is different from other expenditures that are actually incurred. Additionally, the rental equivalence category is the only category that is affected by top coding. We estimate that 3.7% of the households in our data are affected by this issue. Since the rental equivalence of owning a home is more likely to be top-coded among higher-income households, our estimated income elasticities for housing might be biased downward.

While these issues should be borne in mind, none of the results in this paper are changed by excluding the housing category, as discussed in the text.

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