Distinguishing Preferences from Perceptions for Meaningful Policy Analysis

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With the rapidly changing policy landscape of late, I have chosen to focus my address on the more stable fundamentals of economic policy analysis in a time of changing methodologies. In the classical dichotomy of purposes for empirical microeconomic analysis—positive versus normative—my focus might be characterized as a revival of normative purposes—identification of policies that make people better off.

My underlying premise is that the normative purpose of economic policies is to improve the well-being of the people who they serve (the fundamental ethical postulate) and the libertarian notion that choices of individuals reflect their preferences. I show that preferences have been identified by imposing arbitrary perception specifications so that estimated relationships are essentially reduced form equations that serve positive but not normative uses. This permits prediction of measured variables (a positive contribution) but fails to identify policies that make people better off (the normative ideal).

First, I show that support for normative policy analysis has been eroded by empirical practices that have turned toward estimation of atheoretic and reduced form equations that fail to identify marginal behavior and underlying preferences. Second, I demonstrate that estimation of behavioral equations derived from optimization theory cannot distinguish preferences from perceptions in microeconomic problems with uncertainty and is thus insufficient for normative policy analysis. Third, I suggest approaches to identify preferences and perceptions that require (1) joint estimation of behavioral and nonbehavioral relationships, (2) inference of distributional structure, and (3) estimation of perception errors. Without progress on these fronts, preferences cannot be identified sufficiently to permit defensible normative welfare and policy analysis.

The Trend Toward Estimation That Can Serve Only Positive Purposes

Agricultural applications at the frontiers of statistical analysis in the 1920s–1930s led pioneers concerned with theoretical issues, like Fisher (1926), Neyman (1923), and Neyman, Iwaszkiewicz, and St. Kolodziejczyk (1935), to emphasize randomization in controlled agricultural field experiments. For agent behavior, however, estimation turned to naturally occurring data. In this setting, Working (1927) soon discovered the importance of "extraneous and complicating factors." This led Schultz (1938) to incorporate them in demand and supply inference. Subsequently, simultaneous equations estimation techniques were developed to identify multiple equation structures using these shifters to correct for joint endogeneity. These techniques subsequently found widespread use in agricultural economics (see Judge's (1977) review).

From that time revealed preference data became the currency of empirical work, especially for economic welfare and policy analysis, where inference of preferences is essential. In contrast, survey or stated preference methods of measuring preferences were viewed skeptically due to potential hypothetical bias (respondents failure to understand questions);

Presidential Address.

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strategic bias (respondents attempts to affect outcomes); and temporal bias (inconsistent discounting), among others (Whitehead and Blomquist 2006).

Practices since the 1990s, however, have tended to replace structural econometrics with the experimental and atheoretic approaches of labor and education. Groups treated with different policies are interpreted as randomized experiments akin to those of the 1920s where factors were arguably controlled, and the (policy) impact is completely characterized by an estimated treatment effect. Related nonparametric and semiparametric methods have led to a false belief that applied work can be done with few assumptions. More seriously, estimated treatment effects on measured variables cannot support economic welfare analysis of hypothetical and marginal policy changes (Rust forthcoming).

Structural econometrics is criticized because it requires too many assumptions, and errors may affect inference of other structural components. However, all econometric work requires assumptions. The difference is whether they are stated explicitly. Using many examples, Keane (forthcoming) demonstrates how "atheoretic experimentalist" work depends on assumptions just like structural analysis. But explicit assumptions permit testing and validation. In reality, the decline of structural approaches may be due to the lack of validation in practice and the extra work they require (theoretical and institutional).

The experimental approach began with randomized lab experiments using university students as subjects (Kagel and Roth 1995). While many replicable results were developed, skepticism remains about how well lab results apply to real world settings due to subjects' experience and background differences (Levitt and List 2007). Field experiments thus moved out of the lab to use experienced real world agents and real economic consequences (e.g., Binswanger 1980). Both similarities and differences in behavior have been found relative to lab experiments, including a dependence on background conditions (e.g., Harrison, List, and Towe 2007). These background conditions complicate the interpretation of data just as Working's (1927) "extraneous and complicating factors" complicated interpretations of early demand data.

The experimentalist camp in econometrics has further attempted to treat many real-world policy contrasts as natural experiments, much as when economists of the 1920s turned to naturally occurring data. Without fully controlled experiments, however, the effects of "extraneous and complicating factors" similar to Working's (1927) supply and demand shifters have been rediscovered (Angrist and Krueger 2001). Corrections for covariates in propensity score matching and difference-in-difference-in-difference approaches now permit consideration of at least a few such shifters (Heckman, Ichimura, and Todd 1998; Imbens 2004; Gruber 1994). However, the remaining view of the structuralist camp in econometrics is that these "low-grade experiments" are used for causal inference, even though the designs are too primitive to justify conclusions (Keane).

Further, most single-equation techniques use instrumental variables (IV) to correct for covariates, but many studies have become cavalier in choosing instruments (Keane). A huge literature now reveals that the bias and inefficiency of IV estimators can be substantial in finite samples depending on the strength of instruments (see Hahn and Hausman (2002) and their references). If instruments have weak or casual correlations with endogenous variables, or variables are included in inappropriate form, then the claimed robustness of atheoretic and reduced form methods may sacrifice considerable finite sample accuracy in addition to identification of preferences. While structural methods have similar problems, explicit assumptions facilitate inference and validation of underlying structures and functional forms and better identify relevant exogenous forces consistent with a plausible and understandable theoretical explanation.

In summary, these modern empirical trends have three important consequences. First, focusing only on estimation of a discrete treatment effect on a measured variable (e.g., income or revenue) forgoes measurement of marginal benefits necessary for policy refinement. Second, the sense of robustness, which is at least in part false, is attained at the expense of structural information necessary to identify preferences and measure the value of the treatment effect on the treated individuals. Third, with atheoretic and reduced form estimation, the properties of estimators can be weak without detection.

These issues are important for food and agricultural policy analysis because our problems tend to have more data and identifiable structure than other areas of economics.

Fundamental Implications of Simultaneous Equations Estimation

To illustrate the importance of structure, consider a simple two-equation simultaneous system where demand in implicit form is $p = \alpha_{11} + \alpha_{12}q + \alpha_{13}z$ and supply is $q = \alpha_{21} + \alpha_{22}p + \alpha_{23}w$, and where p is price, q is quantity, z is a demand shifter, and w is a supply shifter (random errors are omitted for convenience). Simultaneous equations estimation theory implies that (1) this system can be estimated in reduced form as $p = \gamma_{11} + \gamma_{12}z + \gamma_{13}w$ and $q = \gamma_{21} + \gamma_{22}z + \gamma_{23}w$ by expressing endogenous variables in terms of exogenous variables; (2) estimates of the reduced form facilitate positive purposes of prediction of endogenous variables but not normative welfare and policy analysis; (3) estimates of the structural parameters (the α_{ij}'s) are necessary for calculation of consumer and producer surplus; and (4) estimation of structural parameters is not possible without econometric identification.

To apply these principles, consider preferences and perceptions as a two-equation system. Preferences transform an agent's outcomes into a criterion maximized by chosen actions (e.g., expected utility). Perceptions map the agent's information into subjective probabilities of outcomes. I show below that typical empirical microeconomic analysis identifies only a reduced form, where preference and perceptions are multiplied together.

The problem may be likened to estimation of supply and demand when p and q are observed only as a product, pq, which permits estimation of only a product of two functions $pq = (\gamma_{11} + \gamma_{12}z + \gamma_{13}w)(\gamma_{21} + \gamma_{22}z + \gamma_{23}w) = \psi_1 + \psi_2 z + \psi_3 w + \psi_4 z^2 + \psi_5 w^2 + \psi_6 wz$. Estimation of the latter equation is insufficient to identify structural parameters (the α_{ij}'s). For example, doubling the γ_{2j}'s and halving the γ_{1j}'s generates the same ψ_k's. Thus, neither the γ_{ij}'s, nor the structural α_{ij}'s are identified by estimates of the ψ_k's. In the same way, estimation of behavioral equations where preferences are multiplied by perceptions prevents identification of both. As a result, policy implications are ambiguous

This example demonstrates how estimation of two functions in product form with one dependent variable (pq) can be used for the prediction of that variable but fails to identify parameters of either function required for economic welfare and policy analysis. My central point is that this is not commonly acknowledged or understood (see Foster, Haltiwanger, and Syverson (2005) for an exception). I next develop this point for a general microeconomic optimization problem.

A Generic Microeconomic Problem

Most interesting policy problems involve some form of uncertainty and the probabilistic perceptions of agents. Suppose an agent's choices are represented by a choice vector $\mathbf{x} \in \mathbf{X}$ and agent preferences follow a utility function $u(\mathbf{x}, \varepsilon)$ where ε is a vector of conditions that are subjectively random when the choice is made, $u_{\mathbf{x}} > 0$, $u_{\mathbf{xx}} < 0$ (subscripts denote differentiation and double subscripts denote a Hessian). Agent perceptions are represented by a probability density $h(\varepsilon)$ defined on support $\mathbf{E}$ satisfying standard properties (h is positive and has a unit integral on $\mathbf{E}$). Both u and h include unknown parameters requiring estimation. Assuming an internal solution, the agent's utility maximization problem, $\max_{\mathbf{x}\in\mathbf{X}} \int_{\mathbf{E}} u(\mathbf{x}, \varepsilon)h(\varepsilon)\,d\varepsilon$ has first-order conditions

$$(1) \qquad \int_{\mathbf{E}} u_{\mathbf{x}}(\mathbf{x}, \varepsilon)h(\varepsilon)\,d\varepsilon = 0.$$

The central point of this paper is that assuming a narrow parametric specification for perceptions (h) causes misestimation of preferences (u) or, conversely, assuming a narrow parametric specification for preferences causes misestimation of perceptions. This occurs because preferences and perceptions appear multiplicatively in behavioral equations (which are defined henceforth as first-order equations, their mathematical equivalent, or reduced-form equations representing their conceptual implications).

PROPOSITION 1 (Artificial Identification). *Suppose agent behavior satisfies equation (1) and the parameters of preferences and perceptions are identified by estimation of behavioral equations. Then, estimated preferences and perceptions are artifacts of arbitrary restrictions.*

Proof: Define any alternative perceptions by a density function $\tilde{h}(\varepsilon)$ that is positive with unit integral on $\mathbf{E}$. Then, $\tilde{u}(\mathbf{x}, \varepsilon) \equiv u(\mathbf{x}, \varepsilon)h(\varepsilon)/\tilde{h}(\varepsilon)$ is an alternative set of preferences such that $\tilde{u}_{\mathbf{x}}(\mathbf{x}, \varepsilon)\tilde{h}(\varepsilon) \equiv u_{\mathbf{x}}(\mathbf{x}, \varepsilon)h(\varepsilon)$; $\tilde{u}_{\mathbf{x}} > 0$; and $\tilde{u}_{\mathbf{xx}} < 0$ follow from $u_x > 0$ and

$u_{\mathbf{xx}} < 0$. Based on equation (1), $\{\tilde{u}(\mathbf{x}, \varepsilon), \tilde{h}(\varepsilon)\}$ generates the same behavior as $\{u(\mathbf{x}, \varepsilon), h(\varepsilon)\}$ for all $\mathbf{x}$. Because the choice of $\tilde{h}(\varepsilon)$ is arbitrary, many alternative specification pairs fit the behavior identically. Identification is achieved only by arbitrary exclusion of these. Q.E.D.

Proposition 1 implies that the redistributing risk described by perceptions and revision of curvature (risk aversion) in preferences are perfect substitutes in fitting behavioral conditions derived from optimization. Thus, an infinite set of alternative pairs of specifications exist that fit estimated behavioral conditions identically. Moreover, differences among equivalent pairs are not trivial. Perceptions can involve arbitrary levels of risk in $\mathbf{E}$ with sufficiently more or less risk aversion in preferences for equivalence.

Further, while a simple proof is given here for transparency, equivalence for each ε is unnecessary. Equivalence is required only of the integrals over $\mathbf{E}$. Thus, many more general specification pairs are also equivalent. Apparent econometric identification suggested by small standard errors when estimating preferences and perceptions based on behavioral conditions is thus a misleading result of arbitrarily excluding specifications that fit the data equally well. Such parameter identification is artificial and indefensible.

PROPOSITION 2 (Failure of Identification). *Suppose a flexible preference specification admits all preferences and a flexible perception specification admits all perceptions among specification pairs that generate identical behavior in Proposition 1. Then, neither is identified even approximately by estimation of behavioral conditions.*

Proof: Let $\{\hat{u}(\mathbf{x}, \varepsilon, \boldsymbol{\alpha}), \hat{h}(\varepsilon, \boldsymbol{\alpha}) \mid \boldsymbol{\alpha} \in \mathbf{A}\}$ represent the set of all possible preference and perception specification pairs that generate identical behavior in Proposition 1, where $\boldsymbol{\alpha}$ is an additional parameter vector that indexes them. Then, $\boldsymbol{\alpha}$ is not identified because behavioral equations fit any given data set identically for all $\boldsymbol{\alpha} \in \mathbf{A}$. Q.E.D.

Proposition 2 implies that the typical approach of using more flexible forms to improve approximation does not help. With sufficiently flexible forms for both preferences and perceptions, neither is identified. Identification fails, not because more observations are needed with more flexibility (the equivalence holds for all $\mathbf{x}$). It fails because preferences and perceptions are confounded just as supply and demand are confounded when pq can be observed only as a multiplicative product.

PROPOSITION 3 (Inappropriate Inference with Unbalanced Flexibility). *Suppose a flexible preference specification admits all possible preferences among specification pairs that generate identical behavior in Proposition 1. If preferences are identified, then estimates are determined indirectly by arbitrary choice of the perception specification.*

Proof: From Proposition 2, identification cannot hold if the joint specification admits all possibilities in $\{\hat{u}(\mathbf{x}, \varepsilon, \boldsymbol{\alpha}) \mid \boldsymbol{\alpha} \in \mathbf{A}\} \times \{\hat{h}(\varepsilon, \boldsymbol{\alpha}) \mid \boldsymbol{\alpha} \in \mathbf{A}\}$. Identification admitting all possibilities in $\{\hat{u}(\mathbf{x}, \varepsilon, \boldsymbol{\alpha}) \mid \boldsymbol{\alpha} \in \mathbf{A}\}$ must impose a specific $\bar{h}(\varepsilon, \boldsymbol{\alpha}) \in \{\hat{h}(\varepsilon, \boldsymbol{\alpha}) \mid \boldsymbol{\alpha} \in \mathbf{A}\}$, which arbitrarily determines which $\hat{u}(\mathbf{x}, \varepsilon, \boldsymbol{\alpha})$ will fit the behavioral equations. Q.E.D.

Proposition 3 reveals a subtle indirect effect whereby apparent identification has likely misled collective economic wisdom regarding behavior and related policy analysis. Imposing a narrow specification on perceptions, as is common, can cause highly misleading estimation of preferences even though small standard errors cause false confidence in estimates. The reverse is also true for narrow preference specifications. If incorrect structure is imposed on one, estimation yields incorrect implications for both.

Practitioners of applied econometrics are well aware that choosing parametric specifications affects estimated forms. For estimating individual functions, however, estimates approximate the true function as the flexibility of parametric forms is increased (e.g., from first-order to second-order approximation). The dramatic difference when two functions are estimated only in multiplicative form is that the form imposed on one determines the form that fits the other (as one function compensates for errors in the other) with no assurance of approximation. Similar confounding problems have been recognized elsewhere in isolated cases: Diamond, McFadden, and Rodriguez (1978) for joint estimation of substitution and technical change in production and Bassman, Molina, and Slottje (1983) for joint estimation of demand- and price-dependent preferences. In both cases, identification was achieved by estimating additional structure.

If the purpose is merely to predict the reduced form product of functions, then separate identification is not necessary. But normative policy analysis purposes are not served without separate identification of preferences and perceptions.

These general theoretical results for microeconomic behavior apply to many if not most of the problems that are central to the important policy issues of our time.

The Consumer Case of Food Safety or Product Quality

Because these meetings are joint with the American Council on Consumer Interests, I start with a consumer example related to recent cases of food contamination, unanticipated pharmaceutical or pesticide characteristics, and tainted toy or biological imports. In such problems, consumer preferences are represented by a utility function defined on quantities of consumed goods and their respective quality or health characteristics, denoted by vectors $\mathbf{x}$ and ε, respectively. To facilitate a transparent illustration, suppose these goods are separable from a composite or numeraire good, z, and that utility is quasilinear in the numeraire so that utility can be expressed as $u(\mathbf{x}, \varepsilon) + z$. Consumer perceptions of product characteristics are represented by a subjective probability density $h(\varepsilon)$ on support $\mathbf{E}$. The consumer's utility maximization problem subject to a budget constraint is $\max_{\mathbf{x},z} \int_{\mathbf{E}} [u(\mathbf{x}, \varepsilon) + z]h(\varepsilon)\,d\varepsilon$ s.t. $\mathbf{px} + z = m$ where m is income and $\mathbf{p}$ is a known price vector for $\mathbf{x}$ relative to the numeraire. Substituting the income constraint, the equivalent unconstrained problem, $\max_{\mathbf{x}} \int_{\mathbf{E}} u(\mathbf{x}, \varepsilon)h(\varepsilon)\,d\varepsilon + m - \mathbf{px}$, has first-order conditions $\int_{\mathbf{E}} u_{\mathbf{x}}(\mathbf{x}, \varepsilon)h(\varepsilon)\,d\varepsilon = \mathbf{p}$.

Virtually, every study of food safety or product quality with revealed preference data involves estimation of behavioral equations based, either implicitly or explicitly, on such first-order conditions. Almost always, a highly specific functional form is imposed on either u or h, if not both, or an arbitrary (usually linear) specification approximates the reduced form. A common assumption is that h is a degenerate distribution implying that the consumer perceives the qualities or health implications of products perfectly or nonstochastically, often beyond scientific knowledge after years of product testing. I know of no studies that consider inference among alternative families of distributions.

Propositions 1–3 imply that imposing seemingly benign specifications as approximations of consumer quality perceptions can have dramatically misleading implications for estimated preferences (the nonzero $\mathbf{p}$ is inconsequential). Estimated quality preferences are thus artifacts of arbitrary assumptions on perceptions because subjective probabilities and curvature of preferences are perfect substitutes in fitting data (among studies that attempt to measure preferences rather than treatment effects).

The policy debate rages about whether FDA standards are high enough; quality controls on imported products are sufficient; greater restrictions or labeling standards should be imposed on genetically modified organisms; or (bio)terrorism safeguards are sufficient. Because estimation of behavioral equations cannot identify preferences without imposing arbitrary assumptions on perceptions, related policy analysis can be expected to produce widely differing preference estimates depending on perception specifications. Thus, conflicting support for both sides of such political issues is not surprising, regardless of whether the specifications are chosen deliberately or naively.

The Producer Case of Risk

Similar failures of identification of preferences and perceptions arise in a host of other applications. In production problems, typical practices impose specific distributional families on prices and production, and specific functional forms on technology.

Virtually all empirical production models can be characterized by a profit specification of the form $\pi = \pi(\mathbf{x}, \varepsilon)$, where $\mathbf{x}$ is a vector of producer choices (input quantities, crop insurance participation, etc.) and ε is a vector representing prices and vicissitudes of production (weather, unproven technologies, etc.) that are random with a subjective density function $h(\varepsilon)$ on support $\mathbf{E}$ when production choices are made.

If the producer has von Neumann-Morgenstern utility $\bar{u}(\pi)$ defined on profit π, then $u(\mathbf{x}, \varepsilon) \equiv \bar{u}(\pi(\mathbf{x}, \varepsilon))$ satisfies Propositions 1–3 assuming $\pi_{\mathbf{x}} > 0$, $\pi_{\mathbf{xx}} < 0$, $\bar{u}_{\pi} > 0$, and $\bar{u}_{\pi\pi} < 0$, or more generally that $u_{\mathbf{x}} > 0$ and $u_{\mathbf{xx}} < 0$. Thus, in virtually all empirical production studies, alternative curvatures in the utility function can substitute perfectly for redistributions in either price or production risk in fitting behavioral equations. Further, because u combines both the curvature of $\bar{u}$ and π, the curvature in one can substitute for curvature in the other, meaning that diminishing marginal returns can substitute with risk aversion (Just and Just forthcoming). While parameter identification may be obtained with arbitrary specifications (as indicated by low standard errors), apparent identification is an artifact of arbitrary exclusion of other nontrivially different specifications of each of these that can fit the data equally well.

Implications for production studies are particularly stark because arbitrary specifications in the literature range from risk neutral preferences to perceptions assuming known prices, specific expectations mechanisms, and/or inflexible risk effects of inputs. To the extent that diminishing marginal returns are underrepresented, risk aversion is overestimated. Conversely, assuming risk neutrality, as in common duality models, causes risk preferences to be incorrectly represented by flexible forms that attribute all curvature to technology (Just and Just forthcoming).

Obviously, such misidentification can cause serious errors in analysis of policies such as crop insurance, which is now a major part of U.S. agricultural policy. Some studies have found that most farmers do not choose to insure crops because of risk aversion, but because of subsidized premiums and adverse selection (e.g., Just, Calvin, and Quiggin 1999). Without identifying preferences, the social benefit of such policies is elusive. One possibility is that risk aversion has been overestimated by under-representing perceptions of diminishing marginal productivity, price risk, or production risk. For example, Just and Peterson (2003) found that no plausible level of risk aversion can explain the magnitude of risk response in some empirical estimates. Proposition 3 provides a plausible explanation.

I conclude that empirical production studies have generated false confidence by both estimating flexible preferences with narrow perception specifications and flexible technology perceptions with narrow preference specifications (such as risk neutrality). Wide conflicts between such models with similar convincing explanations of data are explained in Proposition 1. Without resolution we cannot defensibly evaluate the benefits of such policies as crop insurance, disaster payments, or price stabilization.

Consumer Investment in Durables

A similar failure of identification occurs for consumer durable choice. For both appliances and vehicles future demand for energy depends critically on previous choices of durables and their characteristics. Durable choice depends on both preferences for the service rendered and perceptions of realized efficiency and future fuel prices.

All else equal, the price of durables typically increase in their efficiency rating, as denoted by $p = p(x)$, $p_x > 0$. Durables are purchased before fuel prices and true efficiency are known. Intensity of use is decided later when these are realized. Let the realized cost per unit of use (e.g., per mile of transportation) follow $c = c(x, \varepsilon)$, $c_x < 0$, where ε reflects the vicissitudes of energy price determination and realized energy efficiency. Consumer perceptions are represented by a subjective probability density $h(\varepsilon)$ on support E.

To eliminate unimportant issues (for transparent illustration), suppose consumer utility is separable in durable use y and the quantities of all other goods represented by a composite or numeraire commodity z. If preferences are quasilinear in the numeraire, so that utility is represented by $\bar{u}(y) + z$, then the consumer's utility maximization problem after the durable purchase is $\max_y \bar{u}(y) + z$ subject to the budget constraint $yc + z + \alpha p = m$ where α is the required rate of payment for the durable. Substituting the constraint, the problem is $\max_y \bar{u}(y) + m - yc - \alpha p$. With an internal solution ($\bar{u}_y > 0$, $\bar{u}_{yy} < 0$), the first-order condition, $\bar{u}_y - c = 0$, yields the optimal use rate after durable purchase given by $y \equiv \bar{u}_y^{-1}(c)$, which is the functional inverse of $\bar{u}_y(y) = c$.

Assuming optimal subsequent behavior, the durable choice problem is thus $\max_x \int_E u(x, \varepsilon)h(\varepsilon)\, d\varepsilon$, where $u(x, \varepsilon) \equiv \bar{u}(\bar{u}_y^{-1}(c)) - \bar{u}_y^{-1}(c)c + m - \alpha p$. Propositions 1–3 apply because this yields the condition in (1) assuming $u_{\mathbf{x}} > 0$ and $u_{\mathbf{xx}} < 0$. Thus, preferences for durable services and perceptions of future energy price possibilities substitute perfectly in fitting data. Further, $u(x, \varepsilon)$ confounds $\bar{u}(y)$ (preferences) and $c = c(x, \varepsilon)$ (realized cost). So, preference and household production curvatures substitute just as preference and production curvatures substitute in fitting production.

Thus, for another wide class of microeconomic problems, preferences and perceptions cannot be identified separately from estimation of behavioral equations alone. Without this identification, normative analyses of policies for energy efficiency, biofuels, oil imports, and emissions depend ambiguously on assumptions. On the other hand, welfare benefits of such policies cannot be measured by reduced form studies that simply focus on targets or treatment effects on measured variables.

Other Microeconomic Problems of Major Policy Interest

Many other problems associated with major policy issues can be represented as a special case of (1) to show that preferences and perceptions are unidentified when estimated using behavioral equations from optimization alone. Examples include human or livestock diseases, federal disaster relief for catastrophic events, stock market bubbles and busts, and long-term issues such as the agricultural debt crisis of the 1980s, the current sub-prime mortgage crisis, and expansion of oil production and refining capacity.

In all these cases imposing a narrow specification on either preferences or perceptions in order to identify parameters achieves results that are artifacts of assumptions. Unlike typical econometric approximations under single function estimation, these artifacts lack approximating properties. This approach is indefensible and can be seriously misleading for normative policy purposes, given the nontrivial alternative specifications that can provide equivalent explanations of the data. So, how can necessary identification for normative purposes be achieved?

Solving the Identification Problem

The identification problem raised in this paper is difficult and will require substantial research. But available precedent suggests some promising directions. I discuss these first in the context of using aggregate data for policy analysis, as has been typical historically, and second in the context of using microlevel data for policy analysis.

Estimation of Additional Structure with Aggregate Modeling

An obvious possibility for aggregate analysis is to use available data to estimate pertinent technical and market relationships that do not depend on preferences. For example, in the consumer durable problem, data are often available to estimate the objective relationships $p = p(x)$ and $c = c(x, \varepsilon)$ with specifications that do not depend on preferences. Similarly, in the production problem, data are usually available to estimate the objective production/profit relationship, $\pi = \pi(\mathbf{x}, \varepsilon)$, and the distribution of ε (production and prices) with specifications independent of preferences. Assuming for the moment that estimated objective relationships sufficiently represent consumers' subjective assessments (a major assumption considered below), joint estimation can identify (approximate) perceptions using these relationships so that behavioral conditions can additionally identify (approximate) preference parameters.

Ironically, forty years ago, a common practice in production economics was to estimate first-order conditions jointly with the production function (Mundlak and Hoch 1965; Zellner, Kmenta, and Dreze 1966). With the rise of duality and flexible forms, however, estimation focused solely on derivatives of profit or cost functions (supplies and demands), which depend on assumed risk-neutral preferences. Even though implied technologies could be recovered in principle by duality, typical studies did not validate or test them against alternative specifications. Thus, empirical practices have moved away from approaches that could address the identification issue by substituting assumptions.

Unlike production, dual estimation for consumers allowed estimation of (second-order) flexible preferences, but at the expense of assuming highly specific perceptions (certain prices and implicitly, certain quality). Rather than generalizing structural modeling of perceptions, empirical modeling of quality has tended toward estimation of treatment effects on measured variables in reduced form and atheoretic models, ignoring the distinction of preferences and perceptions. Thus, empirical practices for consumers have also moved away from the structural modeling required to identify preferences and perceptions (see Foster and Just (1989) for an exception).

In contrast to prior practice, however, solving the identification problem for both producers and consumers calls for more careful identification of distributional forms of perceptions. Proposition 1 shows how a cavalier assumption as simple as symmetry can seriously limit which preference structure fits behavioral equations. Crop insurance is a rare area in which distributional identification has received attention due to the critical role of tails. Just and Weninger (1999) show that statistical distinction is difficult because measuring random deviations depends on correctly estimating expectations. In contrast, most perception specifications have focused only on the mean in naïve, adaptive, futures, or rational expectations that ignore distributional form. While ARCH/GARCH modeling has added refinement, normality has been commonly assumed arbitrarily. Proposition 3 implies that identifying distributional form is critical for identifying preferences because redistributions substitute perfectly with altered preferences in fitting data. Estimated preferences will approximate reality only to the extent that assumed distributions do so.

A more difficult issue involves identifying deviations of agents' perceptions (both distributions and functional forms) from their objective counterparts estimated from observed data. Use of empirical distributions cannot mitigate this type of misspecification because actual outcomes may not reflect a priori subjective perceptions. The behavioral economics literature has shown increasingly that errors in perceptions can be critical. Errors among agents do not necessarily wash out on average. Anomalous actions following a debt crisis or a commodity boom (or any relevant highly-publicized event) likely cause a mass skewing of perceptions. These issues are likely of growing importance in an era of increasing volatility and overshooting. Bayesian decision theory offers some useful alternatives to modeling perceptions objectively whereby future data do not influence earlier perceptions and more recent data have higher weight (Just 1977). But further development of perception modeling independent of preferences is needed.

Elicitation of Perceptions in Microlevel Modeling

Until recently, proven patterns of anomalous behavior originating with Kahneman and Tversky (1979) were regarded as a refutation of standard utility theory. Many took these to invalidate economic welfare analysis and the normative potential of the revealed preference paradigm (Ariely, Loewenstein, and Prelec 2003). However, two recent papers motivated by the behavioral economics literature suggest further possibilities for identification when objective models do not represent subjective perceptions.

While anomalies have led behavioral economists to introduce nonutility generalizations, Bernheim and Rangel (2008) have introduced the concept of ancillary conditions as an explanation of anomalies. This makes preferences of agents sufficiently observable in revealed preference data to permit normative analysis. Although they overemphasize the libertarian principle for unusual cases of irrational behavior, their approach offers insights for practical policy issues. A major class of ancillary conditions is imperfect perceptions. Imperfect perceptions, if ignored, are falsely attributed to preferences or construed as anomalous preferences.

In another paper, Kzegi and Rabin (2007) recognize the lack of identification of preferences in problems of dichotomous choice. Attempting to rehabilitate normative possibilities under behavioral anomalies, they propose a theory of revealed mistakes, which provides practical interpretation for some important practical classes of Bernheim and Rangel's (2008) ancillary conditions.

Kzegi and Rabin (2007) propose elicitation of perceptions to identify nonobjective perceptions that are otherwise characterized as anomalies. Accepting the possibility that people make mistakes in perceptions is far more sensible than abandoning assumptions that allow normative analysis respecting people's values. The structural modeling of mistakes by eliciting problem-relevant perceptions permits the identifying capacity of behavioral equations to be used to identify preferences following Propositions 1–3.

These elicitations, however, are required of the same agents that generate the revealed preference data. This restricts the approach to microlevel data unless a random sample is used to characterize the distribution of perceptions in aggregate data. While elicitation calls for a considerable expansion of traditional data collection, the feasibility of this approach was demonstrated by Just, Calvin, and Quiggin (1999), who used a survey of perceptions piggy-backed onto the old Farm Cost and Returns Survey. This separation of preferences from perceptions allowed adverse selection incentives for crop insurance participation to be differentiated from risk aversion incentives.

While elicitation raises concerns about hypothetical, strategic, and temporal bias, this approach is proposed here only to remove a major ambiguity in revealed preference data analysis. Slightly biased perceptions may be far superior to the present practice of imposing arbitrary assumptions. Also, the science of framing questions that minimize such bias has become quite refined. In contrast, hypothetical bias is a much greater problem for elicitation of preferences (Young 1979; Hazell 1982).

Other Approaches Involving Experimentation

The experimental literature has also focused recently on joint identification of preferences and perceptions (beliefs), but by imposing specific relationships (see Tversky and Kahneman (1992) and studies listed in Kagel and Roth (1995)). Because experimental data represents optimizing behavior, Propositions 1–3 apply just as for naturally occurring data (imposing a narrow specification on either function or the relationship between them causes arbitrary results). Some experiments have attempted to measure both beliefs and preferences by paying subjects according to the accuracy of stated beliefs in addition to payments for other decisions (combining experiments). But concerns have arisen about confounding of results due to hedging (Blanco et al. 2008). Thus, similar identification problems appear to afflict experimental data both in the lab and field (although possibly in more narrowly controlled settings). A narrowing of experimental conditions and potential conjunctive use of experimental and revealed preference data offer promise for improving identification (List 2006a,b), but further research is required.

Conclusions

The premise of this paper is that normative policy analysis is a major purpose of empirical microeconomic analysis. Results show that innumerable "as if" models fit behavioral equations of wide classes of microeconomic problems equivalently with vastly different implications for preferences. Expected profit maximization may fit data well when risk aversion is highly important or risk aversion may appear significant when profit maximization applies depending on various other specifications. This ambiguity can explain wide conflicts among empirical policy analyses. Economic analysis is often discounted in policy debates due to conflicting results. The failure to identify preferences and perceptions in confounded specifications is arguably a major explanation.

Modern approaches that estimate flexible forms for preferences assuming highly specific perceptions, or vice versa, likely misrepresent both preferences and perceptions. By comparison, however, the more recent tendency to estimate treatment effects on measured variables with reduced form and atheoretic models offers no identification of preferences and perceptions as required for normative policy analysis. Identifying preferences and perceptions separately is essential for normative policy analysis. A reliable solution requires supplementing the usual estimation of behavioral equations with other structural estimation. Using more flexible specifications or obtaining more observations cannot solve the problem.

An obvious approach with aggregate data that has historical precedent is to augment structure with physical relationships independent of behavior. But eliminating arbitrary implications for estimated preferences requires (1) more effort to identify distributional forms because they substitute perfectly with preference forms in fitting data and (2) more effort to identify nonobjective errors in subjective perceptions. Microlevel data supplemented with perception elicitation offer possibilities for uncovering errors in perceptions and identifying mass skewing of perceptions that likely follow unusual circumstances. By isolating errors in perceptions, these approaches can also explain some of the practical behavioral anomalies that have been used to criticize utility theory, welfare economics, and normative policy evaluation. The development of these approaches (1) should become a priority if meaningful normative policy analysis is to be achieved and (2) will not become a priority until the problem is fully recognized.

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