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The Priced Survey Methodology

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Abstract

In this paper, I introduce a novel methodology to conduct surveys. The priced survey methodology. Like standard surveys, priced surveys are easy to implement, and measure invisible assets such as feelings, happiness, knowledge, views, and attitudes on numerical scales. Unlike standard surveys, priced surveys allow to leverage decades of research on revealed preference and consumer demand in the analysis of invisible assets.
JEL C9, D91, C44

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1 Introduction

Many fundamental drivers of choice such as price or income are observable realities. Others, such as feelings, happiness, knowledge, views, attitudes, intentions or reasoning are not. In social sciences, we often rely on integer scales to measure these invisible assets but this creates several important issues.[1] First, as demonstrated by Bond and Lang (2019), cardinal comparisons of average levels measured through integer scales may not be robust to simple monotonic transformation of the scales. Second, it is not possible to disentangle the mechanisms explaining the expression of invisible assets, as measured through survey questions. For example, one might partially misreport her feelings, knowledge, attitudes or

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[1] Stantcheva (2022) provides a recent overview on the use of surveys in economics.

beliefs for various reasons that have to do with the data collection process or the topics of the survey. Third, similar to observable assets, invisible assets are articulated in complex ways, something that cannot be easily captured through independent survey questions.

In this paper, I introduce a novel methodology to measure invisible assets - the priced survey methodology - and show that it gives one solution to all previous challenges. Like standard surveys, priced surveys are easy to implement and rely on numerical scales. Unlike standard surveys, priced surveys allow to leverage the vibrant economic research on revealed preference and consumer demand that developed since Samuelson (1938, 1948) in the analysis of invisible assets.

The basic idea of a priced survey is to add a price structure to a survey. A price structure is characterized by a budget in tokens and associates a price to each question in a given survey. Subjects are given various opportunities to fill the same survey under different price structures. Hence, priced surveys mimic revealed preference experiments implemented in the economic literature, where subjects are offered repeated opportunities to allocate a budget between different consumption goods (e.g., Andreoni and Miller (2002)). To the extent that subjects are rational, their preferences over invisible goods can be recovered (Afriat (1967)). This creates many potential applications. In the rest of this paper, I formally introduce the priced survey methodology and discuss several broad applications.

2 The Methodology

Let $\mathcal{I} = \{1, \dots I\}$ denote a set of subjects, and $\mathcal{S} = \{1, \dots S\}$ a survey of S questions asking subjects to report a subset of their invisible assets on numerical scales. For example, question s might be "All things considered, are you happy with your life these days? Please answer on a scale from 0 to $N(s)$". A subject i's answer to the survey can be represented by a vector $\mathbf{q_i} = \{q_{i,s}\}_{s \in S} \in \prod_{s \in \mathcal{S}} \{0, \dots N(s)\}$, where $N(s) > 0$ is the highest numerical level that can be reported on the scale associated to question s.

In the methodology, subjects first answer a survey without a price structure. A survey without a price structure is referred to as a standard survey in the rest of the paper. Subject i's answer to the standard survey is denoted $\mathbf{q_{i,0}}$. Subjects are then offered repeated opportunities to fill the same survey under different price structures that are experimentally set. Let $\mathcal{K} = \{1, \dots K\}$ be the index set of observations. The price structure of observation k is denoted $(R_k, \mathbf{p_k})$, with $R_k \in \mathbb{N}_+$ a budget in tokens and $\mathbf{p_k} = \{p_{k,s}\}_{s \in \mathcal{S}} \in \mathbb{R}^S_{++}$ a price vector. In observation k, subjects have R_k tokens to allocate to the survey, and increasing the answer to question s by one numerical unit costs $p_{k,s}$ tokens. I denote $q_{i,k,s} \in \{0, \ldots N(s)\}$ subject i's answer to statement s in observation k and $\mathbf{q_{i,k}} = \{q_{i,k,s}\}_{s \in S}$ his vector of answers. Finally, $D_i = \{\mathbf{q_{i,k}}, \mathbf{p_{i,k}}\}_{k \in \mathcal{K}}$ gives the set of data observed for subject i. By assumption, in any observation k, subjects are constrained to saturate their budget constraint.[2]

This design mimics revealed preference experiments. Instead of spending resources by choosing quantities of consumption goods, subjects pay certain prices to express invisible assets, e.g., happiness level, trust in institutions or religiosity. In this context, preferences reflect a subjective organization of thoughts, feelings, views, opinions or attitudes. They correspond to the broad subjective rules governing the expression of invisible assets. In contrast, the prices of invisible assets reflect the aggregate influence of all the factors that weigh on the expression of invisible assets, as measured through survey questions. The following generalized definitions of revealed preferences enables to set axiomatic basis for subjects' rationality.[3]

Definition 1 *Let $\mathbf{v} \in [0,1]^K$. For subject $i \in \mathcal{I}$, an observed bundle $\mathbf{q_{i,k}} \in \prod_{s \in \mathcal{S}} \{0, \ldots, N(s)\}$ is*

1. *$\mathbf{v}$-directly revealed preferred to a bundle $\mathbf{q}$, denoted $\mathbf{q_{i,k}} R^0_{\mathbf{v}} \mathbf{q}$, if $v_k \mathbf{p_{i,k}} \mathbf{q_{i,k}} \geq \mathbf{p_{i,k}} \mathbf{q}$ or $\mathbf{q} = \mathbf{q_{i,k}}$.*

2. *$\mathbf{v}$-strictly directly revealed preferred to a bundle $\mathbf{q} \in \prod_{s \in \mathcal{S}} \{0, \ldots, N(s)\}$, denoted $\mathbf{q_{i,k}} P^0_{\mathbf{v}} \mathbf{q}$, if $v_k \mathbf{p_{i,k}} \mathbf{q_{i,k}} > \mathbf{p_{i,k}} \mathbf{q}$.*

3. *$\mathbf{v}$-revealed preferred to a bundle $\mathbf{q}$, denoted $\mathbf{q_{i,k}} R_{\mathbf{v}} \mathbf{q}$, if there exists a sequence of observed bundles $(\mathbf{q_j}, \mathbf{q_k}, \ldots, \mathbf{q_m})$ such that $\mathbf{q_{i,k}} R^0_{\mathbf{v}} \mathbf{q_j}$, $\ldots \mathbf{q_m} R^0_{\mathbf{v}} \mathbf{q}$.*

4. *$\mathbf{v}$-strictly revealed preferred to a bundle $\mathbf{q}$, denoted $\mathbf{q_{i,k}} P_{\mathbf{v}} \mathbf{q}$, if there exists a sequence of observed bundles $(\mathbf{q_j}, \mathbf{q_k}, \ldots, \mathbf{q_m})$ such that $\mathbf{q_{i,k}} R^0_{\mathbf{v}} \mathbf{q_j}$, $\ldots \mathbf{q_m} R^0_{\mathbf{v}} \mathbf{q}$ and at least one of them is strict.*

If $v_k = 1$ for any $k \in \mathcal{K}$, the previous definition gives the standard direct revealed preference relations (e.g., Varian (1982)); if $v_k = 0$, the revealed preference relations are vacuous, as no observation can be revealed preferred to another. Parameter v_k can be

[2] This assumption is made so that subjects make tradeoffs when they answer the survey in any given observation.

[3] These definitions are taken from Halevy, Persitz and Zrill (2018).

thought of as the minimum difference between the expenditure on bundle $\mathbf{q_{i,k}}$ and the expenditure on bundle $\mathbf{q}$ before $\mathbf{q}$ can be considered worse than the observed choice. We can introduce the notion of consistency for data sets:

Definition 2 *Let $\mathbf{v} \in [0,1]^K$. A dataset D_i satisfies the general axiom of revealed preference given $\mathbf{v}$ (GARP$_\mathbf{v}$) if for every pair of observed bundles, $\mathbf{q_{i,k}} R_\mathbf{v} \mathbf{q}$ implies not $\mathbf{q} P^0_\mathbf{v} \mathbf{q_{i,k}}$.*

Other concepts of consistency could be introduced.[4] As the experimental methodology mimics revealed preference experiments on consumption goods, existing procedures can be used to recover preferences.

3 Applications

3.1 Recoverability of Preferences

The parametric methods to recover preferences are motivated by this result established by Halevy, Persitz and Zrill (2018), which generalizes Afriat's (1967) theorem:[5]

Theorem 1 *The following conditions are equivalent:*

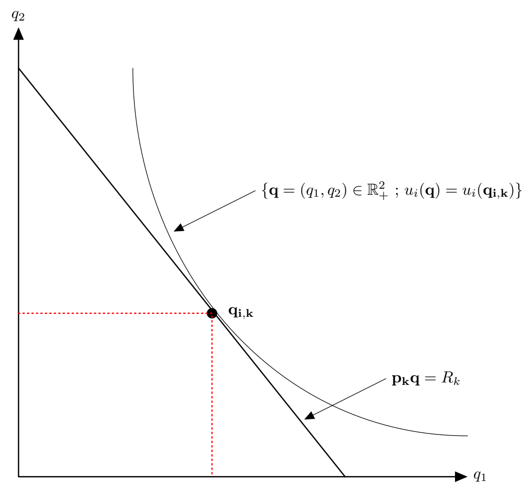
1. *There exists a nonsatiated utility function that $\mathbf{v}$-rationalizes the data.*
2. *The data satisfy GARP$_\mathbf{v}$.*
3. *There exists a continuous, monotone, and concave utility function that $\mathbf{v}$-rationalizes the data.*

From Theorem 1, the data can be $\mathbf{v}$-rationalized by a variety of utility functions. Denoting u_i a utility function, it $\mathbf{v}$-rationalizes subject i's choices when $u_i(\mathbf{q_{i,k}}) \geq u_i(\mathbf{q})$ for any $\mathbf{q_{i,k}}$ and any $\mathbf{q} \in \{\mathbf{q_{i,l}}\}_{l \in \mathcal{K}}$ such that $v_k \mathbf{p_k}.\mathbf{q_k} \geq \mathbf{p_k}.\mathbf{q}$. In the case where $\mathbf{v} = \mathbf{1}$, $S = 2$, and $u_i(.)$ is strictly concave, subject i's decision can be represented as in figure 1. Subject i's optimal choice lies in the indifference set with the highest utility level of any point on the budget constraint $\mathbf{p_k}.\mathbf{q} = R_k$.

[4] The Strong Axiom of Revealed Preference (SARP) might turn out important if researchers rely on expansion paths to increase the precision of their predictions (Blundell et al. (2015)).

[5] Diewert (1973), Varian (1982), and Polisson and Renou (2016) provide various statements and proofs of Afriat's Theorem.

Figure 1: Utility maximization



Estimating utility functions allows to assess how invisible assets are articulated in a subject's choices. As an example, consider CES utility functions of the form:

$$u_i(\mathbf{q}) = \left(\sum_{s=1}^{S} a_{i,s} q_s^{\rho_i} \right)^{1/\rho_i}, \tag{1}$$

with $\mathbf{q} = \{q_s\}_{s \in \mathcal{S}}$, $\rho_i \leq 1$, $a_{i,s} \in [0,1]$ and $\sum_{s=1}^{S} a_{i,s} = 1$. Together, the parameters $\mathbf{a_i} = \{a_{i,s}\}_{s \in \mathcal{S}}$ and ρ_i describe how the different invisible assets in the survey $\mathcal{S}$ work together for subject i. They give a measure of subject i's social norms or worldviews. Parameter $a_{i,s}$ corresponds to the weight of asset s for subject i. Parameter ρ_i captures the convexity of subject i's preferences through the elasticity of substitution, $\sigma_i = 1/(\rho_i - 1)$. In the limit case where $\sigma_i \to \infty$, the assets in $\mathcal{S}$ are perfect substitute for agent i. In the limit case where $\sigma_i \to 0$, the assets in $\mathcal{S}$ are complement for subject i and (1) converges to the Leontief utility function. In the case where $\sigma_i = 1$, (1) converges to the Cobb-Douglass utility function. For example, if $\mathcal{S}$ is a set of questions that measure subjects' attitudes with respect to religion, politics and gender roles, then we might expect attitudes to show some degree of complementarity across these dimensions (i.e. σ_i might be low). By contrast, if $\mathcal{S}$ measures opposite attitudes (e.g., liberal versus conservative attitudes), then one might expect these attitudes to be substitute.

Large surveys such as the World Value Surveys often include many disparate questions. Hence, before estimating utility functions such as (1), it is important to separate out invisible assets in different categories. In standard surveys, invisible assets can be separated using principal component analysis. The resulting categories gives useful indicator of social norms. For example, indicators of social liberal or conservative values can be built by grouping views about gender equality, immigration, same-sex marriage, divorce, death penalty, or abortion (e.g., Norris and Inglehart (2019)). However, these categories are built using correlation patterns, and say little about how subjects group invisible assets when making decisions. In priced surveys, the weak separability tests traditionally used in the analysis of consumer demand can be exploited to separate goods in different categories. These tests have been developed, for example, by Varian (1982), Fleissig and Whitney (2008), and Cherchye et al. (2015) and can directly be applied to priced surveys.[6]

A group of assets is said to be weakly separable if the marginal rate of substitution between any two goods in the group is independent from the quantities consumed of any asset outside this group (Leontief (1947), Sono (1961)). Marginal rates of substitutions capture the utility tradeoffs that the subjects face. Some subjects might face a utility tradeoff between happiness and social status one the one hand, and face a separate utility tradeoff between religiosity and earnings. For these subjects, social status is achieved at the expense of happiness only, while religiosity is perceived as achieved at the expense of higher earnings. For other subjects, happiness, earnings and social status might not be separated. Happiness would be perceived as achieved at the expense of both earnings and social status.

Finally, the priced survey methodology allows to build non-parametric tests for utility models traditionally used to study invisible assets. In the context of social identity for example, Shayo (2020) argues that there exists a fundamental utility tradeoff between gains from identifying to a social group and the distance from that social group. Accordingly, more identification from the working class to national identity is predicted to reduce the working class' support for redistribution (Shayo (2009)). Using the priced survey methodology, this utility tradeoff can be estimated given that preferences over redistribution and national pride are recovered.[7] Other examples of utility models that could be tested using

[6]Other useful tests can also be applied to priced surveys, including homotheticity, additive separability, and homothetic separability. These tests can be found in Varian (1983).

[7]While there are potentially many ways to do so, one simple alternative consists in asking the two following questions. Question 1 asks "How much would you agree with the following statement on a scale from 0 to 10: we need larger income differences as incentives for individual effort". This question captures views about redistribution. Question 2 asks "How much do you agree with the following statements [1: Agree strongly; 2. Agree; 3 Neither agree nor disagree; 4. Disagree, 5. Disagree strongly.] The world would be a better place if people from other countries were more like the people in [Subject's country]". This question gauges feelings of national pride. Both questions are taken from the World Value Survey, and enable researchers to recover preferences over redistribution and national pride.

priced survey methodologies include general models of identity and their many applications stemming from Akerlof and Kranton (2000), models of parenting (e.g., Doepke and Zilibotti (2017), Attanasio, Cunha and Jervis (2019), Seror (2022)), cultural transmission (Bisin and Verdier (2001)), political attitudes and various invisible assets such as ethical norms (Fedderson, Gailmard and Sandroni (2009)), views about globalization (Rodrik (2021)), or emotions (Passarelli and Tabellini (2017)).

3.2 Recoverability of Imputed Prices

In social sciences, it is often challenging to assess experimenter-demand effect, self-censorship and other similar phenomena to interpret measures of invisible assets, e.g., political attitudes, identity, feelings, or happiness.[8] In this section, I show that the priced survey methodology allows to elicit the constraint that weighs on subjects' answers at the time the data are collected. The basic idea is to estimate the price vector that makes any subject i's answers to the standard survey $\mathbf{q_{i,0}}$ consistent with his behavior in the data set D_i. These prices give direct estimates of the constraint that weighs on subject i's answer to any question in the survey $\mathcal{S}$ at the time the data are collected, e.g., the price of expressing a feeling, a political opinion or a view about race.

The set of prices at which subject i's answers to a standard survey are consistent with his behavior in the data set D_i is denoted $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ and is characterized as:

Definition 3 *Given any vector* $\mathbf{q_{i,0}}$ *and a dataset* D_i*, we define the set of prices that* $\mathbf{v}$*-support* $\mathbf{q_{i,0}}$ *by:*

$$S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0) = \{\mathbf{p_0} : (\mathbf{p_k}, \mathbf{q_{i,k}}), k = 0, \dots K, \ \textit{satisfies } (v_0, \mathbf{v})\textit{-GARP and } \mathbf{p_0}\mathbf{q_{i,0}} = 1\}$$

The requirement $\mathbf{p_0}\mathbf{q_{i,0}} = 1$ is a normalization. Subjects' rationality when they answer the standard survey is denoted $v_0 \in [0, 1]$ and is not observed. If v_0 is set to 0, no observation can be revealed preferred to $\mathbf{q_{i,0}}$, so any price vector $\mathbf{p_0}$ such that $\mathbf{p_0}\mathbf{q_{i,0}} = 1$ can support $\mathbf{q_{i,0}}$. Experimenters may approximate v_0, using measures of subjects' rationality in the

[8]Methods have been developed in the experimental literature to assess experimenter-demand effects (e.g., de Quidt, Haushofer and Roth (2018)). When self-censorship biases survey answers, researchers use different data to identify invisible assets. For example, Atkin, Colson-Sihra and Shayo (2021) use food consumption to identify the salience of religious and ethnic identity. Seror and Ticku (2021) use data on enrollment in priestly studies in Catholic seminaries to identify the effect of same-sex marriage laws on the expression of homosexual identity.

priced surveys (see Section 3.4). The set $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ can be derived by solving a set of linear inequalities:

Algorithm 1

- *Input:* D_i, v_0, *and* $\mathbf{q_{i,0}}$.
- *Output:* $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$.

1. *Set* $S_0(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0) = \{\mathbf{p_0} : \mathbf{p_0}\mathbf{q_{i,0}} = 1\}$ *and* $k = 1$
2. *If* $v_k\mathbf{p_k}\mathbf{q_{i,k}} \geq \mathbf{p_k}\mathbf{q_{i,0}}$, *set* $S_k(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0) = \{\mathbf{p_0} \in S_{k-1}(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ *such that* $v_0\mathbf{p_0}\mathbf{q_{i,0}} \leq \mathbf{p_0}\mathbf{q_{i,k}}\}$ *and go to 4.*
3. *If* $v_k\mathbf{p_k}\mathbf{q_{i,k}} > \mathbf{p_k}\mathbf{q_{i,0}}$, *set* $S_k(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0) = \{\mathbf{p_0} \in S_{k-1}(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ *such that* $v_0\mathbf{p_0}\mathbf{q_{i,0}} < \mathbf{p_0}\mathbf{q_{i,k}}\}$ *and go to 4.*
4. *If* $k < K$, *set* $k = k + 1$ *and go to 2.*
5. *If* $k = K$, *return* $S_K(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$.

Algorithm 1 derives the set of price vectors $\mathbf{p_{i,0}}$ that make the answer $\mathbf{q}_{i,0}$ consistent with all the decisions made by subject i. In step 1 of the algorithm, the prices that support $\mathbf{q_{i,0}}$ are assumed included in the hyperplane defined by the budget constraint. This is the largest set that can possibly support $\mathbf{q_{i,0}}$. After step 1, the algorithm proceeds by elimination. It goes through each data point $(\mathbf{p_k}, \mathbf{q_{i,k}})$, $k \in \{1, \ldots K\}$. As the algorithm goes through observation $(\mathbf{p_k}, \mathbf{q_{i,k}})$, if $\mathbf{q_{i,k}}$ is revealed directly preferred to $\mathbf{q_{i,0}}$ (i.e., $v_k\mathbf{p_k}\mathbf{q_{i,k}} \geq \mathbf{p_k}\mathbf{q_{i,0}}$), then $\mathbf{q_{i,0}}$ cannot be revealed directly strictly preferred to $\mathbf{q_{i,k}}$, so $v_0\mathbf{p_0}\mathbf{q_{i,0}} \leq \mathbf{p_0}\mathbf{q_{i,k}}$. Hence, the set $S_k(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ can be characterized as the subset of $S_{k-1}(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ that makes all the observations up to k and $(\mathbf{p_0}, \mathbf{q_{i,0}})$ satisfy $\text{GARP}_{v_0,\mathbf{v}}$. As the algorithm reaches step K, the data set $(\mathbf{p_0}, \mathbf{q_{i,0}}) \cup D_i$ satisfies $\text{GARP}_{v_0,\mathbf{v}}$ for any vector $\mathbf{p_0} \in S_K(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$.

Three remarks are in order. First, the tightness of the set $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ depends on the rationality $\mathbf{v}$. If subjects are not rational and $\mathbf{v} = \mathbf{0}$, then any price vector can support $\mathbf{q_{i,0}}$.[9] Finally, if there are only few observations for which $\mathbf{q_{i,k}}$ is revealed preferred to $\mathbf{q_{i,0}}$, then not much can be learnt from the data on the prices that support $\mathbf{q_{i,0}}$ because the conditions 2 and 3 of Algorithm 1 are often not satisfied.

[9] Formally, for any pair of vectors $\mathbf{v}, \mathbf{u} \in [0, 1]^{K+1}$, if $\mathbf{v} \geq \mathbf{u}$ (meaning that for any $k \in \{0, \ldots, K\}$ $v_k \geq u_k$), then $S(\mathbf{q_{i,0}}, \mathbf{u}, D_i, v_0) \subseteq S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$.

There are two ways to improve the precision of the non-parametric prediction of the prices that support $\mathbf{q_{i,0}}$. First, experimenters can tailor the price structures to a known estimate of $\mathbf{q_{i,0}}$, so that the inequality $\mathbf{p_k}.\mathbf{q_{i,0}} < v_k \mathbf{p_k} \mathbf{q_{i,k}}$ is likely verified for as many observations as possible.[10] Second, similar to consumer demand analysis, knowledge of expansion paths can substantially increase the tightness of the set $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i)$ (Blundell, Browning and Crawford (2008)).[11]

Finally, when the data D_i are used to recover a parametric utility function $u_i(.)$, it is possible to get a parametric estimate of the prices that support $\mathbf{q_{i,0}}$. Indeed, in such cases, $\mathbf{q_{i,0}}$ can be interpreted as the outcome of a utility-maximizing behavior:

$$\mathbf{q_{i,0}} = \underset{\mathbf{q} \in \prod_{s \in \mathcal{S}} [0, N(s)]}{\arg\max} \; u_i(\mathbf{q}) \text{ subject to } \mathbf{p_i}.\mathbf{q} = 1, \tag{2}$$

where $u_i(.)$ is the utility function estimated for subject i. The imputed price $p_{i,s}$ corresponds to the cost of marginally increasing the answer to question s for subject i.[12] The imputed budget is normalized to one without loss of generality.

Fact 1

- *For any* $i \in \mathcal{I}$ *and any vector* $\mathbf{q_{i,0}}$*, there exists a price vector* $\mathbf{p_{i,0}}$ *such that* $\mathbf{q_{i,0}} = \arg\max_{\mathbf{q} \in \prod_{s \in \mathcal{S}} [0, N(s)]} u_i(\mathbf{q})$ *under the constraint* $\mathbf{p_{i,0}}.\mathbf{q} \leq 1$.
- *For any* $s \in \mathcal{S}$, $p_{i,0,s} = \frac{1}{\lambda} \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}}$ *if* $0 < q_{i,0,s} < N(s)$*, and* $p_{i,0,s} \geq \frac{1}{\lambda} \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}}$ *(resp.* $p_{i,0,s} \leq \frac{1}{\lambda} \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}}$*) if* $q_{i,0,s} = 0$ *(resp.* $q_{i,0,s} = N(s)$*), given* $\lambda \geq 0$ *the Lagrange multiplier associated with the optimization problem (9).*

To the extent that $\mathbf{q_{i,0}}$ is not on a corner (i.e., $0 < q_{i,0,s} < N(s)$ for any $s \in \mathcal{S}$), and given subject i's continuous, monotone, and concave utility function $u_i(.)$, there is a unique vector of imputed prices that i faces when answering the survey.[13] In the standard survey, if subject i's answers to a pair (s, z) of questions is not on a corner, then the ratio $p_{i,0,s}/p_{i,0,z}$ is

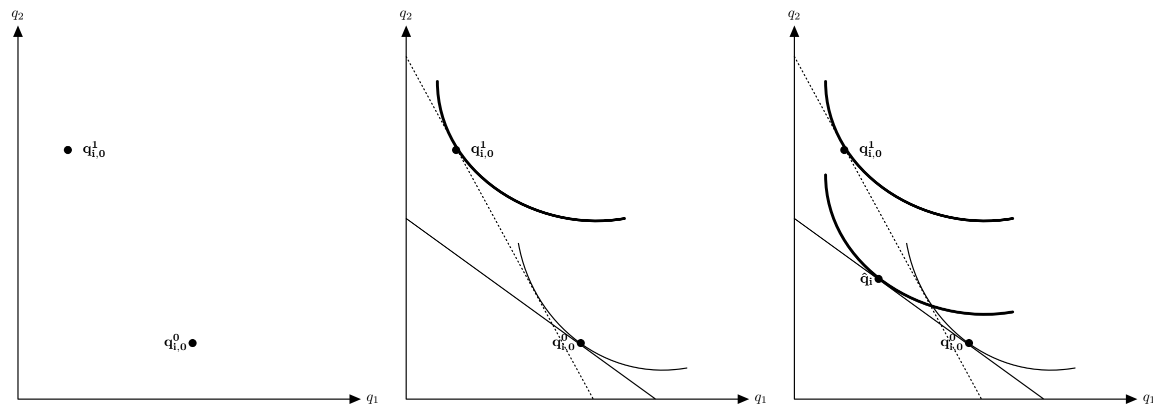
[10] The experimental design could tailor the price structures to the observation of $\mathbf{q_{i,0}}$ for each individual in order to make the set $S(\mathbf{q_{i,0}}, \mathbf{v}, D_i, v_0)$ as precise as possible.

[11] Improving the precision of the prediction of the imputed price might require assuming that the data D_i satisfies a generalized version of the Strong Axiom of Revealed Preference ($\text{SARP}_\mathbf{v}$) rather than $\text{GARP}_\mathbf{v}$ (Blundell et al. (2015)).

[12] The support of $u_i(.)$ is assumed to be the continuous set $\prod_{s \in \mathcal{S}} [0, N(s)]$ so that imputed prices could even be recovered for non-integer values of $\mathbf{q_{i,0}}$.

[13] Equivalently, we could normalize one price instead of the budget and Fact 1 will hold. I chose to normalize the budget because imputed prices are more easy to interpret than imputed budgets.

Figure 2: Decomposition



simply equal to the marginal rate of substitution between these two assets $\frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}} / \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,z}}$. In the standard survey, if subject i's answer to question s is zero (resp. $N(s)$), then the possible values of $p_{i,0,s}$ are bounded from below (resp. from above), $p_{i,0,s} \geq \frac{1}{\lambda} \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}}$ (resp. $p_{i,0,s} \leq \frac{1}{\lambda} \frac{\partial u_i(\mathbf{q_{i,0}})}{\partial q_{i,0,s}}$).

3.3 Interpreting Treatment Effects

Many studies seek to document how interventions or experimental treatments impact happiness, attitudes, feelings or perceptions, among other invisible assets. However, measuring treatment effects through standard surveys conflates two fundamental mechanisms. One is related to changes in subjects' preferences, and one is related to changes in the prices that subjects face when answering the survey. In this section, I show that using the priced survey methodology, it is possible to additively decompose a treatment effect into two components. One related to changes in prices (e.g., the treatment increases the price of expressing xenophobic attitude), and one related to changes in preferences (e.g., the treatment cultivates a more tolerant worldview). The external validity of experimental results might crucially depend on whether treatments primarily change prices or preferences.

In this section, I assume that subjects are evenly and randomly assigned to one of two groups. Let T_i be a dummy variable that is equal to 1 if subject i is randomly assigned to the treatment group and 0 otherwise. I define

$$\mathbf{q_{i,0}} = \begin{cases} \mathbf{q^0_{i,0}} \text{ if } T_i = 0 \\ \mathbf{q^1_{i,0}} \text{ if } T_i = 1 \end{cases} \quad \text{and } \mathbf{p_{i,0}} = \begin{cases} \mathbf{p^0_{i,0}} \text{ if } T_i = 0 \\ \mathbf{p^1_{i,0}} \text{ if } T_i = 1 \end{cases} \tag{3}$$

The basic argument behind the decomposition is represented in Figure 2. As represented in the left panel, vector $\mathbf{q^0_{i,0}}$ (resp. $\mathbf{q^1_{i,0}}$) measures subject i's answer to the standard survey when i is not treated (resp. is treated). Using data from the standard survey, researchers can estimate the treatment effect, defined as the average difference between $\mathbf{q^1_{i,0}}$ and $\mathbf{q^0_{i,0}}$ across subjects. Using priced surveys, preferences and imputed prices can be recovered for any subject. As represented in the middle panel, both $\mathbf{q^1_{i,0}}$ and $\mathbf{q^0_{i,0}}$ can be interpreted as resulting from the maximization of a utility function subject to a budget constraint. Moreover, using the recovered utility functions and imputed prices, researchers can estimate the counterfactual $\mathbf{\hat{q}_i}$, defined as the answer that subject i would have given if her preferences were affected by the treatment but not the price constraint weighing on her answer. As represented in the right panel, using this counterfactual, the treatment effect can be decomposed into a treatment effect due to changes in preferences (the difference between $\mathbf{\hat{q}_i}$ and $\mathbf{q^0_{i,0}}$), and one due to changes in prices (the difference between $\mathbf{q^1_{i,0}}$ and $\mathbf{\hat{q}_i}$).

The vector $\mathbf{\hat{q}_i}$ cannot be observed empirically, as we cannot simultaneously observe subject i's budget constraint when she is not treated and her preferences when she is. However, it is possible to use the data to estimate $\mathbf{\hat{q}}$, a counterfactual for any individual i. $\mathbf{\hat{q}}$ can be estimated either through a parametric approach or through a non-parametric approach.

In the parametric approach, the counterfactual $\mathbf{\hat{q}}$ can be found by solving the following problem:

$$\mathbf{\hat{q}} = \underset{\mathbf{q}\in\prod_{s\in\mathcal{S}}[0,N(s)]}{\arg\max}\ \overline{u}^1(\mathbf{q}) \text{ under the constraint } \mathbf{q}.\overline{\mathbf{p}}_0 = 1, \tag{4}$$

with $\overline{u}^1$ a representative utility function for the treatment group, and $\overline{\mathbf{p}}_0$ the average imputed price vector in the control group.[14] Deriving a unique counterfactual $\mathbf{\hat{q}}$ requires restricting the sample to interior answers, so that Fact 1 characterizes a unique imputed price vector for each individual $i \in \mathcal{I}$. In the Appendix, I give an algorithm to compute a non-parametric counterfactual set $\mathbf{\hat{Q}}$, defined as the set of answers to the standard survey that are (i) consistent with the aggregate data in the treatment group and (ii) generated by an (average) imputed price compatible with answers in the control group. $\mathbf{q_{i,0}}$ is

[14]The representative utility function for the treatment group can be estimated by relying on the average value of the utility parameters in that group.

decomposed into two components, $\mathbf{x_i}(\hat{\mathbf{q}})$ and $\mathbf{w_i}(\hat{\mathbf{q}})$:

$$\mathbf{x_i}(\hat{\mathbf{q}}) = \begin{cases} \mathbf{q^0_{i,0}} \text{ if } T_i = 0 \\ \hat{\mathbf{q}} \text{ if } T_i = 1 \end{cases} \quad \text{and } \mathbf{w_i}(\hat{\mathbf{q}}) = \begin{cases} \hat{\mathbf{q}} \text{ if } T_i = 0 \\ \mathbf{q^1_{i,0}} \text{ if } T_i = 1. \end{cases} \tag{5}$$

In this decomposition, $\mathbf{x_i}(\hat{\mathbf{q}})$ measures how the treatment affects preferences, and $\mathbf{w_i}(\hat{\mathbf{q}})$ measures how the treatment affects prices. $\mathbf{q_{i,0}}$ can be expressed as:

$$\mathbf{q_{i,0}} = \boldsymbol{\alpha} + \boldsymbol{\beta} T_i + \boldsymbol{\eta_i} \tag{6}$$

in the case of constant treatment effects, where $\boldsymbol{\eta_i} = \{\eta_{i,s}\}_{s\in\mathcal{S}}$ is a vector of random variables that I assume identical and independently distributed.

Fact 2 *The treatment effect $\boldsymbol{\beta}$ can be additively decomposed into two vectors, $\boldsymbol{\beta} = \boldsymbol{\beta_1}(\hat{\mathbf{q}}) + \boldsymbol{\beta_2}(\hat{\mathbf{q}})$ with $\boldsymbol{\beta_1}(\hat{\mathbf{q}})$ the average treatment effect associated with the estimation of*

$$\boldsymbol{w_i}(\hat{\mathbf{q}}) = \boldsymbol{\alpha_1} + \boldsymbol{\beta_1} T_i + \boldsymbol{\epsilon_i}, \tag{7}$$

and $\boldsymbol{\beta_2}(\hat{\mathbf{q}})$ the average treatment effect associated with the estimation of

$$\boldsymbol{x_i}(\hat{\mathbf{q}}) = \boldsymbol{\alpha_2} + \boldsymbol{\beta_2} T_i + \boldsymbol{\mu_i}, \tag{8}$$

with $\boldsymbol{\mu_i}$ and $\boldsymbol{\epsilon_i}$ two vectors of i.i.d random variables.

The proof is detailed in the Appendix. The vector $\boldsymbol{\beta_1}(\hat{\mathbf{q}})$ corresponds to the average treatment effect on subjects' preferences keeping their budget constraint equal to its average in the control group. The vector $\boldsymbol{\beta_2}(\hat{\mathbf{q}})$ corresponds to the average treatment effect on subjects' budget constraint, keeping their preferences equal to their "average" in the treatment group. In a non-parametric approach, given that the counterfactual set $\hat{\mathbf{Q}}$ is not a singleton, one can deduce a set of decompositions, applying Fact 2 for all the vectors $\hat{\mathbf{q}}$ that belong to $\hat{\mathbf{Q}}$.[15]

To summarize, this section shows that using data from priced surveys and the corresponding standard surveys allows to decompose any treatment effect into two components. One measures the treatment effect due to changes in preferences, and one measures the treatment effect due to changes in prices. The procedure is based on the estimation of

[15] It is not necessarily true that $\hat{\mathbf{Q}}$ is convex, so the set of decompositions might not be convex either.

a counterfactual. I developed a parametric approach above, which provides a unique decomposition. A non-parametric approach can be a useful complement to the parametric approach, and is developed in the Appendix.

Besides the decomposition, priced surveys allow to assess how the structure of preferences affect the magnitude of a treatment effect. As a simple example, we might expect that interventions seeking to affect one attitude, e.g., anti-vaccine attitude, to be less effective if that attitude complements more entrenched attitudes not targeted by the intervention, e.g., low trust in science, government and institutions.

Finally, using the priced survey methodology, experimenters can assess the welfare implications of experimental treatments (e.g., cultivating altruistic preferences through a given treatment might decrease subjects' welfare). Typically, experimenters could estimate and compare the indirect utility before and after a treatment. One common cardinalization of the indirect utility in consumer behavior is Samuelson's money metric function, which allows to express changes in well-being in monetary units.[16] Depending on whether imputed prices before or after the treatment are considered, this approach leads to the compensating variation or the equivalent variation (Hicks and Allen (1934)).

3.4 Rationality

Is there a rationality behind the expression of feelings, happiness, knowledge, and other invisible assets? Using priced surveys, indices of rationality traditionally used in consumer demand can be computed for invisible assets. Varian (1990) suggested the following measure of rationality in his analysis of consumer demand:

$$\mathbf{v_i} = \min_{\mathbf{v}=\{v_k\}_{k\in\mathcal{K}}\in[0,1]^K, D_i \text{ satisfies GARP}_{\mathbf{v}}} \sum_{k=1}^{K} (v_k - 1)^2, \tag{9}$$

which measures the extent of utility-maximizing behavior implied by the data set D_i. Afriat's (1972) critical cost efficiency index is the lower bound of the vector $\{v_{i,k}\}_{k\in\mathcal{K}}$ that

[16] On the welfare analysis of consumer behavior relying on revealed preference, see Samuelson (1938, 1948), Afriat (1967), Diewert (1973), Varian (1982), Blundell, Browning and Crawford (2008), and Blundell et al. (2015).

solves (9).[17] If $\mathbf{v_i}$ is close to $\mathbf{1}$, then agent i behaves almost rationally in the priced surveys. Parameter $v_{i,k}$ can be interpreted as the fraction of tokens that a subject is "wasting" by making choices that are inconsistent with observation k.

Other measures of rationality can be built, based on violations of GARP (or similar measures of rationality). The money pump index developed by Echenique, Lee and Shum (2011) measures the severity of violations of GARP, assessing the money that arbitragers can "pump" from irrational subjects. Houtman and Maks's (1985) inconsistency index computes the minimal subset of observations that should be removed from the data set D_i in order to eliminate cycles in the revealed preference relation.

Assessing subjects' rationality can be useful for several reasons. First, parametric methods to recover subjects' preferences over invisible assets can be based on the mazimization of subjects' predicted rationality (Halevy, Persitz and Zrill (2018)). Second, rationality measures allow to perform robustness checks by restricting the sample to the most rational subjects. This can be especially important in experimental studies where treatments affect subjects' rationality, as it becomes unclear whether treatment effects are driven by changes in prices, preferences, or rationality.[18] Third, it is possible to evaluate the correlates of rationality in the analysis of invisible goods.[19] Finally, combined with weak separability tests, researchers can evaluate whether there are subcategories of invisible assets for which subjects are more rational than for other subcategories.[20]

4 Discussion

In this paper, I introduced a novel methodology to measure invisible assets - the priced survey methodology. It consists in giving subjects various opportunities to fill the same survey under different price structures. Subjects reveal their preferences over invisible assets

[17] As observed by Halevy, Persitz and Zrill (2018), Afriat's (1972) critical cost efficiency index can be characterized as

$$\mathbf{v_i} = \min_{\mathbf{v}=\{v_k\}_{k\in\mathcal{K}}\in\mathcal{I}, D_i \text{ satisfies GARP}_{\mathbf{v}}} \sum_{k=1}^{K}(v_k-1)^2,$$

with $\mathcal{I} = \{\mathbf{v}\in[0,1]^K : \mathbf{v} = v\mathbf{1}\forall v\in[0,1]\}$.

[18] In that respect, it seems important in experimental studies to design interventions in such a way that subjects' rationality remains constant across treatment groups.

[19] See Echenique, Lee and Shum (2011) and Choi et al. (2014) for studies on the demographic variables that correlate with rationality in consumer demand.

[20] Is there a meta-rationality behind the determination of the categories where subjects' behavior is irrational? This question, close to the issue of self-motivated thinking (Bénabou and Tirole (2002)), could potentially be tested too, using priced surveys.

in priced surveys, so the vibrant economic research on revealed preference and consumer demand that developed since Samuelson (1938, 1948) can be leveraged to study choices over invisible assets.[21]

I suggest three broad applications of priced surveys. First, I give several guidelines for the recoverability of preferences over invisible assets. Second, I show that priced surveys can be used to elicit the constraint that weighs on subjects' answers at the time the data are collected. This can be useful for experimental studies seeking to disentangle whether treatment effects on invisible assets are explained by changes in preferences (e.g., the treatment cultivates a more tolerant worldview) or changes in prices (e.g., the treatment increases the price of expressing xenophobic attitudes). Finally, I detail how subjects' rationality can be assessed, using standard measures established in the revealed preference literature (Afriat (1972), Varian (1990), Houtman and Maks (1985)).

Other potentially useful applications are not discussed in this paper. First, the dynamics of revealed preferences over invisible assets could be assessed, following works in demand analysis by Crawford (2010), or Demuynck and Verriest (2013). Such dynamic analysis could enrich our understanding of the evolution of happiness, depressive feelings, or extremist values among many others. The intergenerational transmission of invisible assets could also be assessed, implementing priced surveys in the appropriate samples. Second, there are several important studies on revealed preferences for multi-person demand behavior (e.g., Chiappori (1988), Brown and Matzkin (1996), Cherchye, de Rock and Vermeulen (2007, 2010, 2011)). Accounting for multi-person demand for invisible assets could be a starting point to an empirical analysis of social interactions and the demand for invisible assets in a general equilibrium framework.

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[21] For a recent review of this literature, see Crawford and De Rock (2014).

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Appendix

A Proof of Fact 2

Proof. Given the random assignment of the subjects across the treatment and control groups,

$$\boldsymbol{\beta} = E(\mathbf{q_{i,0}} \mid T_i = 1) - E(\mathbf{q_{i,0}} \mid T_i = 0), \tag{A.1}$$

which can be rewritten

$$\boldsymbol{\beta} = E(\mathbf{q_{i,0}} \mid T_i = 1) - \hat{\mathbf{q}} + \hat{\mathbf{q}} - E(\mathbf{q_{i,0}} \mid T_i = 0). \tag{A.2}$$

By definition of $\mathbf{x_i}$ and $\mathbf{w_i}$,

$$\begin{aligned} E(\mathbf{q_{i,0}} \mid T_i = 1) &= E(\mathbf{w_i} \mid T_i = 1) \\ E(\mathbf{q_{i,0}} \mid T_i = 0) &= E(\mathbf{x_i} \mid T_i = 0) \\ E(\mathbf{x_i} \mid T_i = 1) &= E(\mathbf{w_i} \mid T_i = 0) = \hat{\mathbf{q}} \end{aligned} \tag{A.3}$$

Hence,

$$\begin{aligned} \boldsymbol{\beta} &= E(\mathbf{w_i} \mid T_i = 1) - E(\mathbf{w_i} \mid T_i = 0) + E(\mathbf{x_i} \mid T_i = 1) - E(\mathbf{x_i} \mid T_i = 0) \\ \boldsymbol{\beta} &= \boldsymbol{\beta_1}(\hat{\mathbf{q}}) + \boldsymbol{\beta_2}(\hat{\mathbf{q}}). \end{aligned} \tag{A.4}$$

■

B Non-Parametric Decomposition

The non-parametric decomposition is based on the estimation of the counterfactual set $\hat{\mathbf{Q}}$. To build this counterfactual set, I first aggregate the data in a given group.

Definition 4 *The aggregate data of treatment group $T \in \{0, 1\}$ is:*

$$D^T = \{(\mathbf{p_k}, \overline{\mathbf{q}}_\mathbf{k}^\mathbf{T})\}_{k \in \mathcal{K}},$$

with $\overline{\mathbf{q}}_\mathbf{k}^\mathbf{T} = \sum_{i \in \mathcal{I}, T_i = T} \frac{2}{I} \mathbf{q_{i,k}}$ the average answer in treatment group T and observation k.

From a standard result in microeconomic theory, an aggregate data set does not necessarily satisfy $\text{GARP}_{\mathbf{1}}$ when the individual-level data sets do. Sufficient conditions can however be derived so that the aggregate data satisfy $\text{GARP}_{\mathbf{1}}$. I abstract from these issues in this proof, and denote $\overline{\mathbf{v}}^{\mathbf{T}}$ the vector such that

$$\overline{\mathbf{v}}^{\mathbf{T}} = \min_{\mathbf{v}=\{v_k\}_{k\in\mathcal{K}}\in[0,1]^K, D^T \text{ satisfies GARP}_{\mathbf{v}}} \sum_{k=1}^{K} (v_k - 1)^2. \tag{A.5}$$

Definition 5 *For any pair of data sets (D^0, D^1), vector $\overline{\mathbf{q}}_{\mathbf{0}}^{\mathbf{0}}$ and rationality level $\overline{v}_0$, the counterfactual set $\hat{\mathbf{Q}}$ is defined as:*

$$\hat{\mathbf{Q}} = \{\hat{\mathbf{q}} \in \prod_{s\in\mathcal{S}} \{1, \dots, N(s)\} : \exists \mathbf{p_0} \in S(\overline{\mathbf{q}}_{\mathbf{0}}^{\mathbf{0}}, \overline{\mathbf{v}}^{\mathbf{0}}, D^0, \overline{v}_0) \textit{ such that } \mathbf{p_0}.\hat{\mathbf{q}} = 1 \textit{ and } \{(\mathbf{p_0}, \hat{\mathbf{q}}) \cup D^1\} \textit{ satisfies } GARP_{(\overline{v}_0, \overline{\mathbf{v}}_{\mathbf{1}})} \}$$

$\hat{\mathbf{Q}}$ is the non-parametric equivalent of $\hat{\mathbf{q}}$, as characterized in (4). It gives all the possible answers that are consistent with the average behavior in the treatment group but generated under an average price vector compatible with subjects' behavior in the control group. Hence, it is as if prices - and rationality level ($\overline{v}_0$) - were on average kept equal to what they are supposed to be in the control group, but choices made consistent with the "agregate" preferences in the treatment group. The algorithm below gives a simple procedure to compute $\hat{\mathbf{Q}}$ for any pair of aggregate data sets (D^1, D^1), average answer to the standard survey in the control group $\overline{q}_0^0$, and rationality $\overline{v}_0$ associated with the average answer $\overline{q}_0^0$.

Algorithm 2

- *Input:* (D^1, D^1), $\overline{v}_0$, *and* $\overline{q}_0^0$.
- *Output:* $\hat{\mathbf{Q}}$.

1. *Set* $z = 1$, $k = 1$,

$$\begin{aligned}\hat{\mathbf{Q}}_0 =& \{\hat{\mathbf{q}} \in \prod_{s\in\mathcal{S}} \{1, \dots, N(s)\} : \exists \mathbf{p_0} \in S(\overline{\mathbf{q}}_{\mathbf{0}}^{\mathbf{0}}, \overline{\mathbf{v}}^{\mathbf{0}}, D^0, \overline{v}_0) \textit{ such that } \mathbf{p_0}.\hat{\mathbf{q}} = 1\} \\ =& \{(\hat{\mathbf{q}}(\mathbf{z})\}_{z\in\{1,\dots,Z\}}\end{aligned} \tag{A.6}$$

and

$$P_0(\hat{\mathbf{q}}(\mathbf{z})) = \{\mathbf{p_0} \in S(\mathbf{p_0}, \overline{\mathbf{v}}^{\mathbf{0}}, D^0, \overline{v}_0) : \hat{\mathbf{q}}(\mathbf{z}).\mathbf{p_0} = 1\} \tag{A.7}$$

2. *If* $\overline{v}_k \mathbf{p_k} \overline{\mathbf{q}}^{\mathbf{1}}_{\mathbf{k}} \geq \mathbf{p_k} \hat{\mathbf{q}}(\mathbf{z})$*, set* $P_k(\hat{\mathbf{q}}(\mathbf{z})) = \{\mathbf{p_0} \in P_{k-1}(\hat{\mathbf{q}}(\mathbf{z}))$ *such that* $\overline{v}_0 \mathbf{p_0} \hat{\mathbf{q}}(\mathbf{z}) \leq \mathbf{p_0} \overline{\mathbf{q}}^{\mathbf{1}}_{\mathbf{k}}\}$ *and go to 4.*

3. *If* $\overline{v}_k \mathbf{p_k} \overline{\mathbf{q}}^{\mathbf{1}}_{\mathbf{k}} > \mathbf{p_k} \hat{\mathbf{q}}(\mathbf{z})$*, set* $P_k(\hat{\mathbf{q}}(\mathbf{z})) = \{\mathbf{p_0} \in P_{k-1}(\hat{\mathbf{q}}(\mathbf{z}))$ *such that* $\overline{v}_0 \mathbf{p_0} \hat{\mathbf{q}}(\mathbf{z}) < \mathbf{p_0} \overline{\mathbf{q}}^{\mathbf{1}}_{\mathbf{k}}\}$ *and go to 4.*

4. *If* $P_k(\hat{\mathbf{q}}(\mathbf{z})) = \phi$ *set* $\hat{\mathbf{Q}}_z = \hat{\mathbf{Q}}_{z-1} \setminus \{\hat{\mathbf{q}}(\mathbf{z})\}$ *and go to 5. Otherwise:*
   - *If* $k < K + 1$*, set* $k = k + 1$ *and go to 5.*
   - *If* $k = K$*, go to 5.*

5. *If* $z < Z$*, set* $z = z + 1$ *and go to 2. Otherwise, return* $\hat{\mathbf{Q}}_Z$*.*

As for Algorithm 1, Algorithm 2 proceeds by elimination. It starts with the set $\hat{\mathbf{Q}}_0$ that contains all the vectors of answers that could be supported by a price that generates an average answer in the control group. The algorithm then eliminates from this set all the elements that will violate $\text{GARP}_{(\overline{v}_0, \overline{\mathbf{v}}^{\mathbf{1}})}$ in the aggregate data set of the treatment group. The algorithm proceeds by elimination, exactly like Algorithm 1. Since $\hat{\mathbf{Q}}_0$ is a hyperplane of $\prod_{s \in \mathcal{S}} \{1, \ldots, N(s)\}$, it can take substantial time to run Algorithm 2 for large surveys or long scales.