Price Search and Consumption Inequality: Robust, Credible, and Valid Inference*

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Abstract

This paper investigates whether heterogeneity in price search mitigates consumption inequality. I propose a model where the consumer can pay weakly lower prices by shopping more intensively. The extent by which shopping intensity decreases prices paid depends on the consumer shopping technology. I show that the model is generically not identified and develop a revealed preference methodology to set identify the shopping technology in a computationally tractable fashion. My approach allows for nonparametric concave preferences, rich heterogeneity, and measurement error in prices. Using a novel statistical framework, I show that data on shopping expenditures from the Nielsen Homescan Dataset are consistent with the model. I document that income groups have comparable shopping intensities and find that they have similar shopping technologies.

1 Introduction

Price search describes the process whereby buyers actively seek to gauge the most favorable prices. Its importance has been recognized at least since the

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seminal paper of Stigler (1961) and has gained strong empirical support over the years.[1] In their influential paper, Aguiar and Hurst (2007) show that the drop in expenditures occurring around retirement, known as the retirement-consumption puzzle, is partly due to older households searching more intensively than younger ones. Likewise, low-income consumers should also search more intensively as they should have a lower opportunity cost of time. Moreover, while differing shopping strategies have been documented across income groups (Griffith et al., 2009), it is unclear if low-income consumers make larger savings than high-income consumers. My paper addresses this gap by investigating whether heterogeneity in price search mitigates consumption inequality.[2]

This paper considers a structural model to set identify the shopping technology. In the spirit of Leamer (1985) and Manski (2003), individual preferences are only restricted to satisfy a mild shape constraint to guarantee the robustness of my inference. Additionally, I address the credibility critique of Angrist and Pischke (2010) by showing that causal inference obtains in my model. I go a step further and show that my model is valid by statistically testing its assumptions through the use of a recent framework due to Schennach (2014). The methodology adopted in this paper allows me to test the instrumental variable approach generally used in the literature. I find that instrument validity is violated in my data set.

The first contribution of this paper is to provide a novel revealed preference methodology to characterize a general model of price search. The model shares key features with the literature such as the concavity of the utility function and the log-linearity of the shopping technology. Using a recent statistical framework, I can test the compatibility of the model in the data. My approach formalizes the empirical evidence documenting (i) the effects of price search on prices paid (Aguiar and Hurst, 2007), (ii) the use of price search as a mechanism to mitigate adverse income shocks (McKenzie et al., 2011; Nevo and Wong, 2019), and (iii) the wide heterogeneity in prices paid (Kaplan and Menzio, 2015; Kaplan et al., 2019; Hitsch et al., 2019). By testing the main assumptions on which the price search literature relies, I provide a foundation for existing models of price search (Aguiar and Hurst, 2007; Pytka, 2017; Arslan et al., 2021) and reinforce the plausibility of their empirical results.

I show that the model is set identified in the sense that many elasticities

[1]See, for example, Sorensen (2000), Brown and Goolsbee (2002), Aguiar and Hurst (2007), and McKenzie et al. (2011). For a general survey, see Baye et al. (2006).

[2]See Attanasio and Pistaferri (2016) for a survey of the literature investigating whether consumption inequality tracks income inequality.

of price with respect to shopping intensity are consistent with the model given the data. This feature is salient more generally such as in the model of Aguiar and Hurst (2007). To address this issue, I provide a procedure to recover the set of elasticities consistent with the model and show that it is convex. The implementation takes advantage of a revealed preference approach (Afriat, 1967; Diewert, 1973; Varian, 1982; Browning, 1989) and its extension to nonlinear budgets (Forges and Minelli, 2009). Accordingly, my results can be applied to nonparametric utility functions and nonlinear budget sets.

In a validation study of the Nielsen Homescan Dataset, Einav et al. (2010) report severe measurement error in prices and provide information about its structure. The presence of measurement error requires special attention for three reasons. First, the model could be compatible with the true data but incompatible with the observed data, hence leading to the erroneous rejection of the model.[3] Second, measurement error can complicate empirical analyses by obscuring the true behavior of variables such as expenditures.[4] Third, measurement error can bias estimators in unpredictable ways. For example, measurement error may not be classical such that bias could arise even if it appears on the dependent variable in a standard regression setting. This is relevant because it implies that the estimation in Aguiar and Hurst (2007) could be biased.

By using the methodology developed by Schennach (2014), I am able to nonparametrically account for measurement error and statistically test the model. Furthermore, the extension of Aguiar and Kashaev (2018) allows me to impose the concavity of the utility function without increasing the dimensionality of the problem. I extend the applicability of their framework to allow for nonlinear budget sets and a mixture of parametric and nonparametric components in the model. This is achieved by using a rejection sampling algorithm in the implementation of the methodology.[5] This method has the advantage to be applicable in a broader set of models while remaining computationally tractable.

The second contribution of this paper is to set estimate the shopping technology while allowing for sizable heterogeneity and measurement error in prices. Following the price search literature, I assume that the shopping technology is log-linear in shopping intensity. However, my estimation allows for individual-specific elasticities, deals with measurement error in prices, and does not rely

[3]Measurement error was shown to reverse conclusions about the validity of exponential discounting in single households (Aguiar and Kashaev, 2018).

[4]See Attanasio and Pistaferri (2016) for an overview of how measurement error can cloud the evolution of consumption inequality.

[5]The rejection sampling algorithm exploits GPU parallel computing when applicable.

on the availability of instrumental variables. My set estimates resolve the uncertainty about the true effects of search on prices paid and explore how they change across various dimensions. Furthermore, I show that instruments such as income violate the exogeneity assumption in my data set.

My model recovers the causal effect of shopping intensity on prices paid by imposing a mild centering condition on the error term of the shopping technology. The validity of this assumption can be jointly tested along with the model. This constitutes a substantial advantage over instrumental variables where the exogeneity restriction is untestable when the independent variable is continuous (Gunsilius, 2020). Since it is often difficult to know whether an instrument is uncorrelated with the error, having a framework to evaluate this assumption is valuable. Furthermore, estimators derived from instrumental variables can be noisy and sensitive to the choice of instrument. In contrast, the partial identification approach taken in this paper is robust.

The shopping technology used by the consumer can be viewed as a function that takes shopping intensity as an input and returns price paid as an output. In this light, the estimation of the shopping technology is related to the estimation of gross production functions. Analogously to Gandhi et al. (2020), the first-order conditions of the problem provide cross-equation restrictions that can be used to identify the shopping technology.[6] In a firm setting, my centering condition amounts to assuming that the average productivity across firms is stable. This allows firm-specific productivity shocks to follow essentially unrestricted processes and may be useful in periods where aggregate productivity is steady.

In my empirical application, I use the Nielsen Homescan Dataset that tracks U.S. households' purchases on each of their trips to a wide variety of retail outlets. As the data set does not have a perfect measure of shopping intensity, I proxy it by shopping trips. This measure captures sales and discounts that can be seized by frequently visiting a store and price variation across stores. The data set also has many demographic variables on each participating household such as their income brackets, education level, and geographic state.

I show that my model is consistent with the Nielsen Homescan Dataset as the statistical test fails to reject the hypothesis that the model generated the data. I document that low-income consumers pay lower prices than high-income consumers despite that their shopping intensity is almost identical. Moreover, I

[6] See also Levinsohn and Petrin (2003) for an earlier treatment on the estimation of gross output production functions and Olley and Pakes (1996) and Ackerberg et al. (2015) for the related problem of estimating value-added production functions.

find that doubling shopping intensity decreases the expected average price paid by about 19.25% on average for both low- and high-income consumers. Thus, price search has no significant role in explaining lower prices paid by low-income consumers. This finding is consistent with Broda et al. (2009) who document that low-income consumers pay lower prices mainly through the purchase of less expensive goods within product categories.

The 95% confidence set on the average elasticity of average price with respect to shopping intensity states that doubling shopping intensity decreases the average price paid by at least 19.1% but no more than 19.5%. This effect is well-above the preferred estimate of 7% obtained by Aguiar and Hurst (2007) using income as an instrument.[7] My results show that the effects of shopping intensity on prices paid are almost three times larger than previously thought. Moreover, they confirm the soundness of the calibration of Arslan et al. (2021) used in a similar model of price search.

The rest of the paper is organized as follows. Section 2 introduces the model and provides testable restrictions. Section 3 describes the data set. Section 4 discusses the environment. Section 5 presents the statistical framework. Section 6 presents the empirical application. Section 7 concludes. The main proofs can be found in Appendix A5.

2 Description of the Model

This section introduces the notation used throughout the paper, presents the model, characterizes its testable implications, and provide a procedure to recover the identified set.

2.1 Notation

The scenario under consideration is that of households making purchases over a certain time window. Let $\{1,\ldots,N\}$, $\{1,\ldots,L\}$, and $\{1,\ldots,T\}$ denote the set of households, commodities, and periods for which data are observable. I will abuse notation and let N, L and T refer to each of these sets. For any household $i \in N$, good $l \in L$ and time period $t \in T$, denote prices by $p_{i,l,t}$, consumption by $c_{i,l,t}$, shopping intensity by $a_{i,l,t}$, and search ability by $\omega_{i,l,t}$. I assume that P, C, $A \subseteq \mathbb{R}^L_{++}$ and $W \subseteq \mathbb{R}^L$, where P, C, A and W correspond to the price, consumption, shopping intensity and search ability spaces, respectively. An observation on a

[7] In addition to correcting the value of the elasticity, my confidence set is also much more precise than the 95% confidence set obtained with instrumental variables.

given household $i \in N$ at time $t \in T$ is a triple $(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t}) \in P \times C \times A$.[8] Accordingly, a data set is written as $\{(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})\}_{t \in T}$.

2.2 The Consumer Problem

In every time period, the consumer is assumed to know her realization of search ability and to choose consumption and shopping intensity accordingly. Formally, consumer $i \in N$ behaves as if maximizing her lifetime utility subject to satisfying her budget constraints:

$$\max_{(\boldsymbol{c}_i, \boldsymbol{a}_i) \in C^T \times A^T} \sum_{t=1}^{T} \delta_i^{t-1} u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t}) \tag{1}$$

subject to

$$\boldsymbol{p}_i(\boldsymbol{a}_{i,t}, \boldsymbol{\omega}_{i,t})' \boldsymbol{c}_{i,t} + s_{i,t+1} = y_{i,t} + s_{i,t},$$

where the instantaneous utility function $u_i : C \times A \to \mathbb{R}$ is continuous, concave, strictly increasing in consumption, and decreasing in shopping intensity; $\delta_i \in [0.95, 1]$ is the discount factor; $s_{i,t+1}$ are savings in a risk-free asset; $\boldsymbol{p}_i(\boldsymbol{a}, \boldsymbol{\omega}_{i,t})$ is the vector of continuously differentiable good-specific price functions $p_{i,l} : A \times W \to P$; $y_{i,t} > 0$ is income; and $\boldsymbol{p}_{i,t} := \boldsymbol{p}_i(\boldsymbol{a}_{i,t}, \boldsymbol{\omega}_{i,t})$. A data set $D_i := \{(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})\}_{t \in T}$ is rationalized by the model if there exist a utility function $u_i(\cdot, \cdot)$, a vector of price functions $\boldsymbol{p}_i(\cdot, \cdot)$, an income stream $(y_{i,t})_{t \in T}$, a savings stream $(s_{i,t+1})_{t \in T}$, and a discount factor $\delta_i \in [0.95, 1]$ such that $(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_{t \in T}$ solves (1). The econometrician is assumed to only observe the data set D_i.

The model has two distinctive features. First, the consumer gets utility from consumption and *disutility* from shopping intensity. The latter captures the opportunity cost of time such as foregone earnings and leisure. Second, the consumer can pay lower prices by shopping more intensively. The extent by which shopping intensity reduces prices paid depends on the consumer ability to take advantage of sales and other deals such as coupons. The consumer problem boils down to finding the optimal trade-off between utility from consumption and disutility from shopping intensity.

This trade-off is illustrated in Figure 1 in the case where there is one good $L = \{1\}$ and one time period $T = \{1\}$. The consumer has to choose a bundle that lies within her budget set $\mathcal{B}_i := \{(\boldsymbol{c}, \boldsymbol{a}) \in C \times A : \boldsymbol{p}_i(\boldsymbol{a}, \boldsymbol{\omega}_i)' \boldsymbol{c} \leq y_i + s_i\}$. This set is represented by the shaded area in Figure 1. Since the utility function is strictly increasing in consumption, the consumer further picks a bundle on the budget

[8] I use bold font to denote vectors and follow the convention that vectors are vector columns.

line. In Figure 1, the affordable bundle that maximizes the consumer utility is (c_i, a_i). At this point, the indifference curve IC_i is tangent to the budget line, hence corresponding to the unique maximizer.[9]

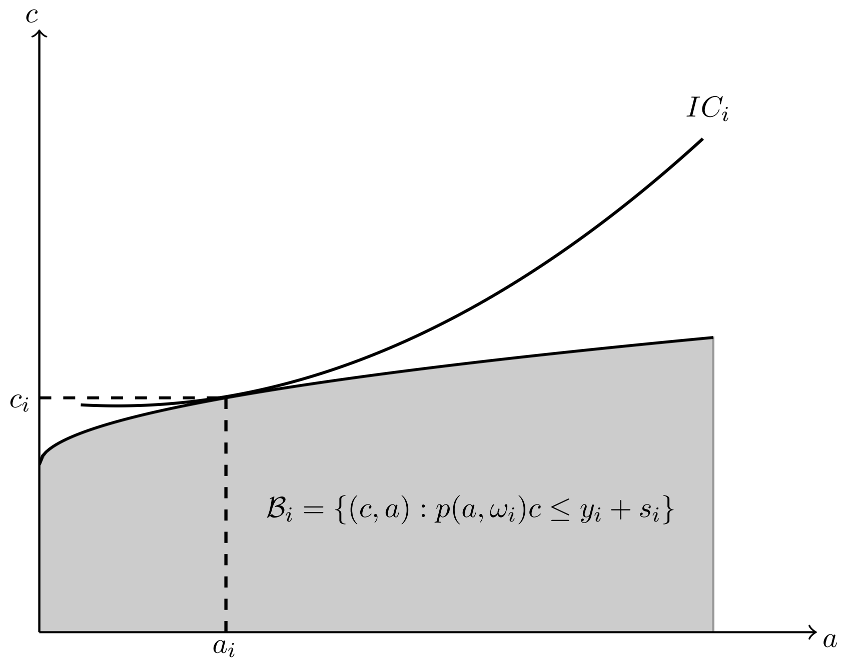

Figure 1: Optimal Choice with Price Search

In the remaining of the paper, I follow the price search literature and assume that the price functions are log-linear in shopping intensity.[10]

Assumption 1. *For all $l \in L$, the log price function is given by*

$$\log(p_{i,l}(a_{i,l,t}, \omega_{i,l,t})) = \alpha_{i,l}^0 + \alpha_{i,l}^1 \log(a_{i,l,t}) - \omega_{i,l,t},$$

where $\alpha_{i,l}^0 \in \mathbb{R}$ denotes the intercept and $\alpha_{i,l}^1 \leq 0$ denotes the elasticity of price with respect to shopping intensity.

Assumption 1 states that log prices decrease linearly in log shopping intensity. Moreover, search ability enters negatively in the price functions such that a higher search ability decreases prices paid. Changing it to enter positively would only reverse the interpretation. Since the price functions are individual-specific, Assumption 1 allows for significant heterogeneity in prices paid including across

[9]In Appendix A1, I show that my model can be extended to home production and relates it to that of Aguiar and Hurst (2007).

[10]See, for example, Aguiar and Hurst (2007) and Arslan et al. (2021).

age, income, and location. Further discussion of Assumption 1 is relayed to Section 4.

2.3 Identified Set

Given a data set D_i, I am interested in what can be learned about the elasticity $\alpha^1_{i,l}$. For any good $l \in L$, the first-order conditions with respect to consumption and shopping intensity are

$$\delta^t \nabla_c u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_l = \lambda_{i,t} p_{i,l,t} \tag{2}$$

$$\delta^t \nabla_a u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_l = \lambda_{i,t} \alpha^1_{i,l} a_{i,l,t}^{\alpha^1_{i,l}-1} e^{-(\omega_{i,l,t}-\alpha^0_{i,l})} c_{i,l,t}. \tag{3}$$

Solving for the exponential function in equation (3) yields

$$e^{-(\omega_{i,l,t}-\alpha^0_{i,l})} = \left(\lambda_{i,t}^{-1} \delta^t \nabla_a u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_l\right) / \left(\alpha^1_{i,l} a_{i,l,t}^{\alpha^1_{i,l}-1} c_{i,l,t}\right).$$

This equation can be substituted into the price function equation for good l to get rid of the intercept and search ability. Further substituting $\lambda_{i,t}^{-1}\delta^t$ by its expression from equation (2) then gives

$$\alpha^1_{i,l}(u_i) = \mathrm{MRS}_{i,l} \cdot \frac{a_{i,l,t}}{c_{i,l,t}} \quad \forall l \in L, \tag{4}$$

where $\mathrm{MRS}_{i,l} := \frac{\nabla_a u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_l}{\nabla_c u_i(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_l} \leq 0$ denotes the marginal rate of substitution and highlights that the consumer would have to receive consumption to increase her shopping intensity.

Equations (4) shows that every preference that generates a distinct marginal rate of substitution induces a distinct shopping technology $\alpha^1_{i,l}$. The set of all elasticities that can be sustained by the model is captured by the identified set.

Definition 1. Under Assumption 1, the identified set is defined by

$$\mathcal{I}(D_i) := \{\boldsymbol{\alpha}^1_i(u_i) : D_i \text{ is rationalized by the model } (1), u_i \in \mathcal{U}\},$$

where $\mathcal{U}$ is the set of utility functions that are continuous, concave, strictly increasing in consumption, and decreasing in shopping intensity.

In words, the identified set contains every elasticity such that data on consumption and shopping intensity can be thought of as maximizers of the consumer problem (1) for some well-behaved preferences.

2.4 Nonparametric Analysis of the Model

This subsection characterizes the testable implications of the model and provides a feasible procedure to recover the identified set. Let $\odot$ denote the Hadamard product such that $(\boldsymbol{x} \odot \boldsymbol{y})_j = x_j y_j$. The following result characterizes the empirical content of the model.

Theorem 1. *Let D_i be a given data set. Then, conditional on a vector of price functions $\boldsymbol{p}_i(\cdot,\cdot)$ satisfying Assumption 1, the statements*

(i) The data set is rationalized by the model, where the utility function $u(\boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})$ is continuous, concave, strictly increasing in $\boldsymbol{c}_{i,t}$, and decreasing in $\boldsymbol{a}_{i,t}$,

and

(ii) There exist numbers $u_{i,t}$, $\lambda_{i,t} > 0$, and a discount factor $\delta_i \in [0.95, 1]$, such that for all $s, t \in T$, the following system of inequalities is satisfied

$$
\begin{aligned}
&u_{i,s} \leq u_{i,t} + \lambda_{i,t}\delta_i^{-t}\left[\boldsymbol{p}'_{i,t}(\boldsymbol{c}_{i,s} - \boldsymbol{c}_{i,t}) + \left(\frac{\partial \boldsymbol{p}_i(\boldsymbol{a}_{i,t}, \boldsymbol{\omega}_{i,t})}{\partial \boldsymbol{a}_{i,t}} \odot \boldsymbol{c}_{i,t}\right)'(\boldsymbol{a}_{i,s} - \boldsymbol{a}_{i,t})\right] \\
&\quad 0 < \boldsymbol{p}_{i,t} \\
&\quad 0 \geq \frac{\partial \boldsymbol{p}_i(\boldsymbol{a}_{i,t}, \boldsymbol{\omega}_{i,t})}{\partial \boldsymbol{a}_{i,t}} \odot \boldsymbol{c}_{i,t},
\end{aligned}
$$

are related in the following way. If (i) then (ii). Moreover, if the budget sets $\{\mathcal{B}_{i,t}\}_{t\in T}$ are convex then (ii) implies (i).

The first set of inequalities in Theorem 1 (ii) represents the core substance of the model, where the numbers $u_{i,t}$ and $\lambda_{i,t} > 0$ can be thought of as utility numbers and marginal utilities of expenditure. The second and third sets of inequalities capture the assumptions that the utility function is strictly increasing in consumption and decreasing in shopping intensity, respectively. The last part of Theorem 1 states that (ii) exhausts the empirical content of the model if the budget sets are convex.

Since the econometrician only observes $\{(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})\}_{t\in T}$, the inequalities in Theorem 1 (ii) cannot be applied directly. In addition to the utility numbers, marginal utilities of expenditure, and discount factor, it is necessary to find numbers for the differentials of the price functions such that the inequalities are satisfied. The following result formalizes the strategy.

Proposition 1. *Let D_i be a given data set. If prices were generated by a vector of price functions $\boldsymbol{p}(\cdot,\cdot)$ satisfying Assumption 1, then D_i satisfies Theorem 1* *(ii) if and only if there exist numbers $u_{i,t}$, $\lambda_{i,t} > 0$, $\alpha^0_{i,l}$, $\alpha^1_{i,l} \leq 0$, $\omega_{i,l,t}$, and a discount factor $\delta_i \in [0.95, 1]$, such that for all $l \in L$ and $s, t \in T$, the following system of inequalities is satisfied*

$$
\begin{aligned}
u_{i,s} &\leq u_{i,t} + \lambda_{i,t}\delta_i^{-t}\left[\boldsymbol{p}'_{i,t}(\boldsymbol{c}_{i,s} - \boldsymbol{c}_{i,t}) + \boldsymbol{\rho}'_{i,t}(\boldsymbol{a}_{i,s} - \boldsymbol{a}_{i,t})\right] \\
0 &< \boldsymbol{p}_{i,t} \\
0 &\geq \boldsymbol{\rho}_{i,t},
\end{aligned}
$$

where $\rho_{i,l,t} := \alpha^1_{i,l} a_{i,l,t}^{\alpha^1_{i,l}-1} e^{-(\omega_{i,l,t}-\alpha^0_{i,l})} c_{i,l,t}$.

Proposition 1 provides testable conditions that the data must satisfy to be rationalized by the model. Since the model is generally set identified, there may be many solutions to the inequalities in Proposition 1. These solutions are observationally equivalent in the sense that the data do not allow us to distinguish one from another.

A consequence of Theorem 1 is that the set of solutions in Proposition 1 directly relates to the identified set.

Corollary 1. *If the inequalities in Proposition 1 are only necessary for the data to be rationalized by the model, then*

$$\mathcal{I}(D_i) \subset \left\{\boldsymbol{\alpha}^1_i : D_i \textit{ satisfies Proposition 1}\right\}.$$

If the budget sets $\{\mathcal{B}_{i,t}\}_{t\in T}$ are convex, then the inequalities in Proposition 1 are sufficient for the data to be rationalized by the model and

$$\mathcal{I}(D_i) = \left\{\boldsymbol{\alpha}^1_i : D_i \textit{ satisfies Proposition 1}\right\}.$$

Corollary 1 states that conservative bounds on the identified set can always be recovered via Proposition 1. Moreover, these bounds are sharp whenever the budget sets are convex. The next result establishes some structure about the set of solutions in Proposition 1.

Proposition 2. *For a given data set $\{(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})\}_{t\in T}$, numbers $(\lambda_{i,t})_{t\in T} \in \mathbb{R}^T_{++}$, and discount factor $\delta_i \in [0.95, 1.0]$, the set of solutions $\boldsymbol{\alpha}^1_i$ in Proposition 1 is convex.*

Proposition 2 implies that the identified set can be recovered by finding the smallest and largest value of $\boldsymbol{\alpha}^1_i$ for which a solution to Proposition 1 exists. This can be achieved by using linear programming at sequential values of $(\lambda_{i,t})_{t\in T}$ and

δ_i. If the budget sets are not convex, then the procedure returns conservative bounds on the identified set.

3 Data

This section presents the data set used in my empirical application and reviews its main source of measurement error.

3.1 Sample Construction

For my empirical application, I use the Nielsen Homescan Dataset 2011 (henceforth, Homescan). This data set contains information on purchases made by a panel of U.S. households in a large variety of retail outlets. The data set is designed to be representative of the U.S. population based on a wide range of annually updated demographic characteristics including age, sex, race, education, and income. Participating households are provided with a scanner device and instructed to record all of their purchases after each shopping trip. The scanner device first requires participants to specify the date and store associated with each trip. Then, they are prompted to enter the number of units bought and the amount saved from coupons for each item scanned. When an item is purchased at a store with point-of-sale data, the average weighted price of the item in that week and store is directly given to Nielsen. Otherwise, panelists enter the price paid prior to any deal or coupon.

The Homescan contains information on Universal Product Codes (UPC) belonging to one of 10 departments. In order to mitigate issues associated with stockpiling, I restrict my attention to the following four food departments: dry grocery, frozen foods, dairy, and packaged meat. This selection leaves over a million distinct UPCs representing about 40% of all products in the Homescan. For each household, I also aggregate the data to monthly observations to further reduce stockpiling issues. The resulting UPC prices are calculated as the average UPC prices weighted by quantities purchased.

To obtain regular observations on each good, I aggregate UPCs to their department categories, yielding a total of four "goods". The resulting aggregated prices are calculated as the average UPC prices weighted by quantities purchased. Even with this layer of aggregation, some households do not have purchases from each category of goods in every month. Since the model requires price observations in every time period, I discard those households from the analysis.

In my empirical application, this aggregation also serves the purpose of reducing the dimensionality of the model.[11]

In addition to the above restriction, I only consider single households. This is motivated by recent evidence that exponential discounting may be rejected because of preference aggregation within a household.[12] Thus, including couple households could lead to the artificial rejection of the model. Finally, I consider consumers that are at least 50 years old to exclude potential online shoppers.

The data set focuses on households that satisfy the above criteria and who participated in the Homescan from April to September of the panel year 2011. The final sample contains 1645 consumers, 4 aggregated goods, and 6 monthly time periods. Additional details about the construction of the data set are provided in Appendix A2.

3.2 Sample Description

To assess whether my constructed sample is in line with the Homescan 2011, Table 1 compares demographics between the two samples.

Table 1: Summary Demographics

	N	Age	White (%)	Black (%)	Asian (%)	Other (%)	Male (%)	Female (%)	High school or less (%)
Sample	1645	65.45	86.14	11.43	0.55	1.88	34.04	65.96	27.90
Homescan 2011	62 092	57.45	83.77	9.38	3.17	3.99	74.99	90.41	46.21

Notes: N is the sample size. Age is calculated using the year of birth of the head household member assumed to be the male unless it is missing.

Table 1 shows that the average age, proportion of females, and education level are slightly higher in my sample than in the Homescan. The difference in age is natural given that my sample is restricted to consumers that are at least 50 years old. Despite the higher proportion of females and higher education level in my sample, the demographics are still fairly representative overall.

The fundamental assumption of the model is that consumers can decrease their prices paid by searching more intensively. To confirm that price search is an empirical feature of the data, Figure 2 displays how log prices vary with log number of shopping trips.

[11] Although the methodology can be applied to any number of goods, the treatment of measurement error necessitates a moderate number of goods for the computations to be tractable.

[12] As Adams et al. (2014) point out, inconsistencies may arise due to negotiation within a couple household. Jackson and Yariv (2015) further show that time inconsistent behavior will appear if individuals in a non-dictatorial household have different discount factors. By accounting for measurement error in survey data, Aguiar and Kashaev (2018) show that single households behave consistently with exponential discounting while couple households do not.

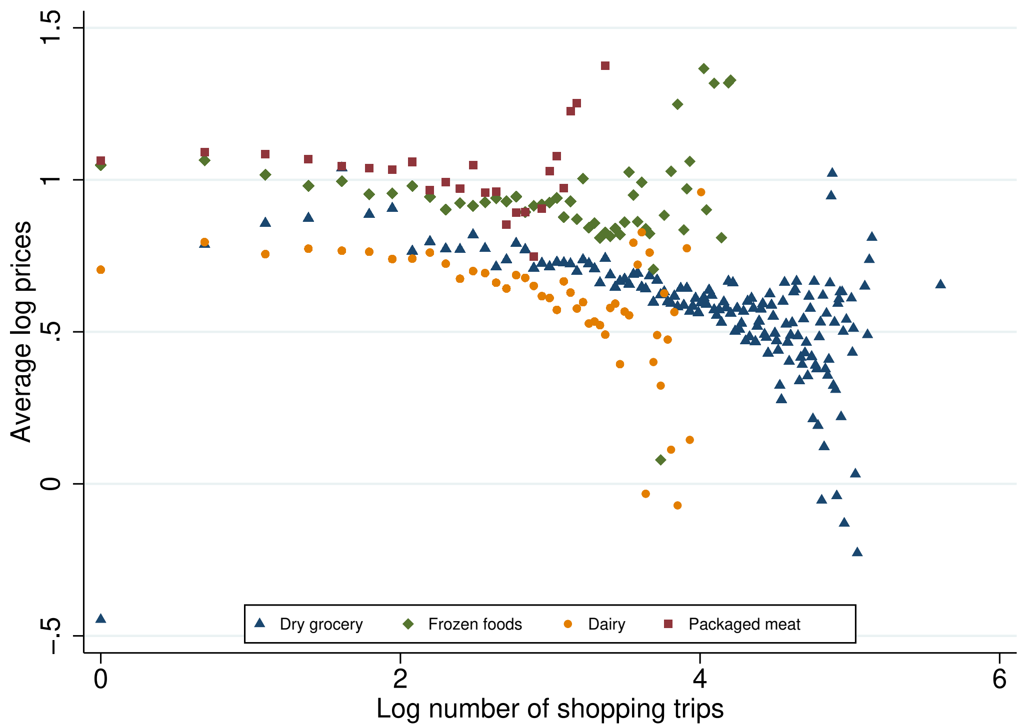

Figure 2: Average Log Price by Log Number of Shopping Trips

Notes: The vertical axis reports the average log price, where the average is taken across consumers.

Consistent with the main hypothesis of the model, Figure 2 shows a clear negative relationship between prices paid and shopping intensity. That said, the true effect of shopping intensity on prices paid may be quite different from the one displayed in Figure 2. Consumers that go on many trips may do so because they do not find satisfactory discounts. This could explain the uptick in prices paid for larger values of shopping trips on frozen foods and packaged meat. Alternatively, those upticks could reflect the purchase of higher quality goods on those shopping trips.

Next, Figure 3 gives additional information on prices paid by comparing differences in log prices paid between high- and low-income consumers.

The overwhelming trend shown in Figure 3 is that, conditional on shopping trips, high-income consumers pay higher prices relative to low-income consumers. Since this feature holds for almost every number of shopping trips, differences in prices paid cannot be attributed to differences in shopping intensity. A plausible reason for the difference could be that high-income consumers purchase goods of higher quality. Yet, a complementary explanation is that low-income consumers

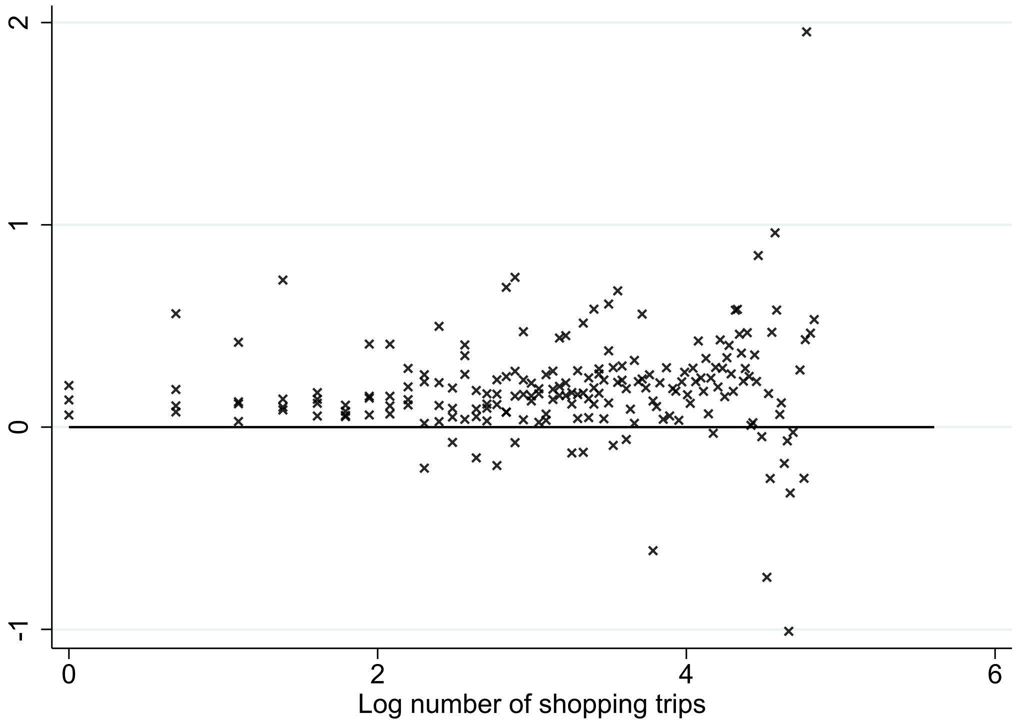

Figure 3: Difference in Average Log Price between Income Groups

Notes: The vertical axis reports the difference in average log price between high- and low-income consumers. The average is taken across consumers belonging to the same income group. High-income consumers are defined as those with an income greater than $50,000. Low-income consumers are defined as those with an income lower than $25,000.

have a greater incentive to take advantage of sales and discounts to increase their real income. That is, low-income consumers could have a better shopping technology such that shopping intensity would be more effective in decreasing prices paid for them than for high-income consumers.

A possible approach to recover the true effects of shopping intensity on prices paid is to use instrumental variables. However, an issue with this approach is that measurement error in prices could yield inconsistent estimators if measurement error is nonclassical or correlated with instruments. More generally, instruments could also fail the exogeneity assumption. In my empirical application, I show that such concerns about instrument validity are justified.

3.3 Measurement Error

The data collection process employed by Nielsen may induce measurement error for three reasons. First, conditional on a shopping trip, entry mistakes may arise as panelists self-report their purchases. Second, when a consumer purchases a

UPC at a store that provides Nielsen with point-of-sale data, the price reported (before coupons) is the weighted average price during that week in that particular store. Thus, the reported price will be different from the price paid if the store changed the price during the week. Third, some consumers have loyalty cards whose discounts are not incorporated into the final price paid.

In a validation study of the Homescan 2004, Einav et al. (2010) use transactions from a large retailer in order to document the extent of measurement error. Consistent with the above observations, they find that price is the variable most severely hit by measurement error. Specifically, they find that around 90% of UPCs are accurately recorded by panelists on average. This number increases to 99% conditional on the quantity being equal to one. In contrast, the accuracy is only around 50% for prices. Accordingly, I focus exclusively on measurement error in prices in my application.

Since prices are mismeasured, observed prices $(\boldsymbol{p}_{i,t})_{t\in T}$ are different from true prices paid by the consumer $(\boldsymbol{p}^*_{i,t})_{t\in T}$. Let the difference between their logarithms define measurement error: $\boldsymbol{m}_{i,t} := \log(\boldsymbol{p}_{i,t}) - \log(\boldsymbol{p}^*_{i,t})$ for all $t \in T$.[13] Using price data from a large retailer, Einav et al. (2010) show that the difference between observed and true log prices is centered around zero in the Homescan 2004. Formally, one cannot reject that the difference in sample means of log prices is zero at the 95% confidence level.

As Nielsen's method of data collection has not changed since their study, I take their finding as support for mean zero measurement error in log prices in the Homescan 2011.

Assumption 2. *For all $l \in L$ and $t \in T$, the following moment condition holds:*

$$\mathbb{E}\left[\log(p_{l,t})\right] = \mathbb{E}\left[\log(p^*_{l,t})\right].$$

Assumption 2 says that expected observed log prices and true log prices are the same for each good and time period. Together, they yield a total of $L \cdot T$ moments on measurement error.

4 Environment

In this section, I discuss existing assumptions and impose additional structure on the model in preparation of the empirical application.

[13]This definition makes no assumption on the way measurement error arises. For example, measurement error could be additive or multiplicative and be correlated across goods or time periods.

Conditional on the log-linear specification implied by Assumption 1, price functions are otherwise free to vary across goods and consumers. This heterogeneity is important as goods may not be subject to the same discounts and consumers may not have access to the same set of stores.[14] Furthermore, note that the price function for any good $l \in L$ only depends on the shopping intensity on that good. This precludes complementarities that may naturally arise, for instance, if two goods are in a same aisle in a store. Since goods are aggregated to coarse categories in the data set, this issue should be largely mitigated.

Consistent with the ability of the consumer to transfer income across time, I restrain the marginal utility of expenditure.

Assumption 3. *For all $t \in T$, the marginal utility of expenditure is constant and such that $\lambda_{i,t} = 1$.*

Assumption 3 requires that the marginal utility of expenditure be invariant to changes in income. This quasilinearity assumption is justified in my empirical application as the data span only a period of 6 months for which unexpected changes in income should be negligible. Besides, the data set focuses on food categories. Hence, changes in income should have mild impacts on preferences regardless of their magnitudes.[15]

The next assumption imposes the average search ability to be time-invariant and ensures that price search is refutable. To see why, note that Assumption 1 implies that the true average price paid must decrease whenever shopping intensity increases if there is no change in the average search ability. Therefore, inconsistencies with price search arise whenever this relationship is violated in the data.[16]

Assumption 4. *For all $t \in T$, $\mathbb{E}\left[\bar{\omega}_t\right] = 0$, where $\bar{\omega}_t$ denotes the average search ability across goods.*

Assumption 4 allows time-varying search ability for specific goods as long as the overall search ability remains constant. Permitting search ability for a particular good to change over time is important in my application because of the coarse aggregation of the data. Indeed, since a consumer may purchase different baskets of goods in different time periods, prices may vary due to variations

[14]Hence, even if store chains apply a nearly-uniform pricing rule (DellaVigna and Gentzkow, 2019), the shopping technology may still differs across consumers.

[15]Quasilinearity is also used by Echenique et al. (2011) and Allen and Rehbeck (2020) in a similar scanner data set on food expenditures.

[16]See Appendix A3 for analytical power results.

in the composition of the baskets of goods. As such, Assumption 4 can be interpreted as requiring the average quality of the baskets of goods purchased to be time-invariant across consumers.

Aside from the above restriction, Assumption 4 is quite general as it does not presume anything about the underlying stochastic process of search ability. Conditional on the aggregate average search ability to be time-invariant, it allows individual-specific search ability to vary arbitrarily with both observables and unobservables. In particular, it includes Markovian processes often assumed in the production function literature.[17]

Given the log-linearity of the price functions, Assumption 4 implies that average log true prices should be around the mean conditional on shopping trips. In accordance with this prediction, Figure 4 shows that the distribution of observed average log prices is centered around its mean. I report the unconditional distribution for expositional purposes; similar shapes obtain for the conditional ones.[18]

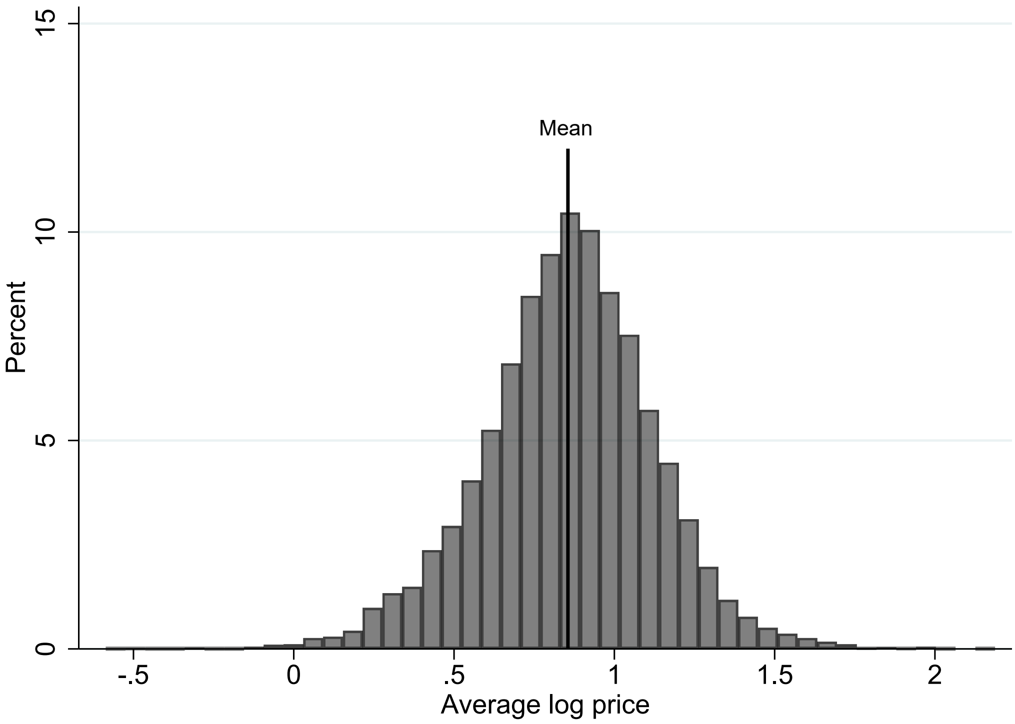

Figure 4: Distribution of Average Log Prices

[17]See, for example, Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and Gandhi et al. (2020).

[18]Consistent with Assumption 1, distributions conditioned on larger values of shopping trips tend to be centered around lower values of log prices.

It is useful to note that, under Assumption 2, measurement error balances out such that the observed mean average log price coincides with the true mean average log price asymptotically. As such, the observed mean average log price shown in Figure 4 can be thought of as the true mean average log price under Assumption 2.

At last, I restrict the support of the elasticity of price with respect to shopping intensity to guarantee that concavity of the utility function can be falsified.

Assumption 5. *For all $l \in L$, $-\alpha^1_{i,l} \in [0, 1]$.*

Assumption 5 constrains the elasticity of price with respect to shopping intensity to be in $[-1, 0]$ for every good $l \in L$. In comparison, Aguiar and Hurst (2007) obtain a point-estimate of -0.07 for the elasticity of average price with respect to shopping intensity using the Homescan 1993-1995.[19] As such, Assumption 5 should give enough flexibility for the need of the data.

Remark. *Measurement error implicitly accommodates various shocks that may occur outside the model. For example, changes in prices induced by supply shocks would be absorbed by the moments on measurement error provided they satisfy Assumption 2. Likewise, exogenous shocks can be absorbed by search ability provided they satisfy Assumption 4. Accordingly, the model is robust to a variety of perturbations.*

5 Statistical Framework

In this section, I extend the deterministic framework presented in the paper to a statistical one susceptible to testing and inference. To this end, I exploit the Entropic Latent Variable Integration via Simulation (ELVIS) methodology of Schennach (2014) and the refinement of Aguiar and Kashaev (2018). I then show that causal inference obtains in the model.

5.1 Characterization of the Model via Moment Functions

From now on, consumer data sets should be viewed as independent and identically distributed draws from some distribution. Let $X := P \times C \times A$ and $E|X$ be the support of the latent random variables conditional on X. Moreover, let $x_i \in X$ denote the observed random data $(\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_{t\in T}$ and $e_i \in E|X$ denote the latent random variables $(u_{i,t}, \delta_i, \boldsymbol{\alpha}_i, \boldsymbol{\rho}_{i,t}, \boldsymbol{\omega}_{i,t}, \boldsymbol{m}_{i,t})_{t\in T}$.

[19] Their estimate is obtained using an instrumental variable approach and is for a single aggregated good.

The methodology of Schennach (2014) requires the model to be expressed through a set of moments. Therefore, for all $l \in L$ and $s, t \in T$, I write the model defined by Assumptions 1-5 by the following moment functions:

$$
\begin{aligned}
&g^u_{i,s,t}(x_i, e_i) := \mathbb{1}\left(u_{i,s} - u_{i,t} - \delta_i^{-t}\left[\boldsymbol{p}^{*\prime}_{i,t}(\boldsymbol{c}_{i,s} - \boldsymbol{c}_{i,t}) - \boldsymbol{\rho}'_{i,t}(\boldsymbol{a}_{i,s} - \boldsymbol{a}_{i,t})\right] \leq 0\right) - 1,\\
&g^p_{i,l,t}(x_i, e_i) := \mathbb{1}\left(\log(p^*_{i,l,t}) - \left(\alpha^0_{i,l} + \alpha^1_{i,l}\log(a_{i,l,t}) - \omega_{i,l,t}\right) = 0\right) - 1,\\
&g^m_{i,l,t}(x_i, e_i) := \log(p_{i,l,t}) - \log(p^*_{i,l,t}),\\
&g^\omega_{i,l,t}(x_i, e_i) := \bar{\omega}_{i,t},
\end{aligned}
$$

where the first set of functions characterizes the concavity of the utility function, the second the log-linearity of the price functions, the third measurement error, and the last search ability. The latent random variables satisfy their support constraints: $\delta_i \in [0.95, 1]$, $-\boldsymbol{\alpha}^1_i \in [0, 1]$, $\boldsymbol{\rho}_{i,t} \leq 0$ and $\boldsymbol{p}^*_{i,t} > 0$, where $\boldsymbol{\rho}_{i,t}$ further satisfies

$$
\boldsymbol{\rho}_{i,t} := \frac{\partial \boldsymbol{p}_i(\boldsymbol{a}_{i,t}, \boldsymbol{\omega}_{i,t})}{\partial \boldsymbol{a}_{i,t}} \odot \boldsymbol{c}_{i,t}.
$$

This equality constraint implies that $\boldsymbol{\rho}_{i,t}$ is completely determined by the data and latent variables $(u_{i,t}, \delta_i, \boldsymbol{\alpha}_i, \boldsymbol{\omega}_{i,t}, \boldsymbol{m}_{i,t})_{t \in T}$.

Every consumer has a total of $T^2 + L \cdot T + L \cdot T + T$ moment functions, written as $\boldsymbol{g}_i(x_i, e_i) := (\boldsymbol{g}^u_i(x_i, e_i)', \boldsymbol{g}^p_i(x_i, e_i)', \boldsymbol{g}^m_i(x_i, e_i)', \boldsymbol{g}^\omega_i(x_i, e_i)')'$ for short. Arbitrary combinations of these sets of functions are written with their superscripts bundled together. For example, $\boldsymbol{g}^{m,\omega}_i(x_i, e_i)$ is the set of functions on measurement error and search ability. Note that the moment functions $\boldsymbol{g}_i(x_i, e_i)$ depend on unobservables. As such, the latent variables have to be drawn from some distribution for the moment functions to be evaluated.

Since Assumptions 2 and 4 only impose centering conditions on the expected measurement error and the expected average search ability, the latent variables are essentially unrestricted for any particular consumer. Therefore, empirical content is gained by averaging the moment functions $\boldsymbol{g}_i(x_i, e_i)$ across consumers.[20] The distribution of the latent variables that satisfy individual-specific moment functions $\boldsymbol{g}^{u,p}_i(x_i, e_i)$ may then only do so when the expectation of $\boldsymbol{g}^{m,\omega}_i(x_i, e_i)$ deviates from zero.

5.2 Statistical Price Search Rationalizability

Let $\mathcal{M}_X$, $\mathcal{M}_{E,X}$, and $\mathcal{M}_{E|X}$ denote the set of all probability measures defined over X, (E, X), and $E|X$, respectively. Moreover, let $\mathbb{E}_{\mu\times\pi}[\boldsymbol{g}_i(x_i, e_i)] :=$

[20] I show that the model defined by Assumptions 1-5 is refutable in A3.

$\int_X \int_{E|X} \boldsymbol{g}_i(x_i, e_i) d\mu d\pi$, where $\mu \in \mathcal{M}_{E|X}$ and $\pi \in \mathcal{M}_X$. The moment functions previously defined allow me to define the statistical rationalizability of a data set with respect to price search.[21]

Definition 2. Under Assumptions 1-5, a random data set $x := \{x_i\}_{i=1}^N$ is price search rationalizable (PS-rationalizable) if

$$\inf_{\mu \in \mathcal{M}_{E|X}} \|\mathbb{E}_{\mu \times \pi_0}[\boldsymbol{g}_i(x_i, e_i)]\| = 0,$$

where $\pi_0 \in \mathcal{M}_X$ is the observed distribution of x.

That is, the data are PS-rationalizable if there exists a distribution of the latent random variables conditional on the data such that the expected moment functions are satisfied. In practice, searching over the set of all conditional distributions represents a daunting task. Fortunately, the following result shows that the problem can be greatly simplified without loss of generality.[22]

Theorem 2. *The following are equivalent:*

(i) A random data set x is PS-rationalizable.

(ii) $\min_{\boldsymbol{\gamma} \in \mathbb{R}^{L \cdot T + T}} \|\mathbb{E}_{\pi_0}[\tilde{\boldsymbol{h}}_i(x_i; \boldsymbol{\gamma})]\| = 0,$

where

$$\tilde{\boldsymbol{h}}_i(x_i; \boldsymbol{\gamma}) := \frac{\int_{e_i \in E|X} \boldsymbol{g}_i^{m,\omega}(x_i, e_i) \exp(\boldsymbol{\gamma}' \boldsymbol{g}_i^{m,\omega}(x_i, e_i)) \mathbb{1}(\boldsymbol{g}_i^{u,p}(x_i, e_i) = 0) d\eta(e_i|x_i)}{\int_{e_i \in E|X} \exp(\boldsymbol{\gamma}' \boldsymbol{g}_i^{m,\omega}(x_i, e_i)) \mathbb{1}(\boldsymbol{g}_i^{u,p}(x_i, e_i) = 0) d\eta(e_i|x_i)},$$

and where $\eta(\cdot|x_i)$ is an arbitrary user-specified distribution function supported on $E|X$ such that $\mathbb{E}_{\pi_0}[\log(\mathbb{E}_\eta[\exp(\boldsymbol{\gamma}' \boldsymbol{g}_i^{m,\omega}(x_i, e_i))|x_i])]$ exists and is twice continuously differentiable in $\boldsymbol{\gamma}$ for all $\boldsymbol{\gamma} \in \mathbb{R}^{L \cdot T + T}$.

Proof. See Theorem 2.1 in Schennach (2014) and Theorem 4 in Aguiar and Kashaev (2018). □

In words, Theorem 2 (*ii*) averages out the unobservables in $\boldsymbol{g}_i(x_i, e_i)$ according to some conditional distribution.[23] The particularity of $\eta(\cdot|x_i)$ is to preserve the set of values that the objective function can take before the latent variables have been averaged out. As such, any minimum achieved under

[21] This definition follows the notion of identified set in Schennach (2014).

[22] See Aguiar and Kashaev (2018) for the weak technical assumptions required for this result to hold.

[23] Schennach (2014) shows the existence of an admissible conditional distribution $\eta(\cdot|x_i)$ and gives a generic construction for it.

μ can also be achieved under $\eta(\cdot|x_i)$. The dimensionality of the problem is then further reduced by noting that the concavity of the utility function and the log-linearity of the price functions are only restricting the conditional support of the unobservables. Thus, one can draw from the conditional distribution $\tilde{\eta}(\cdot|x_i) := \mathbb{1}(\boldsymbol{g}_i^{u,p}(x_i,\cdot) = 0)\eta(\cdot|x_i)$ rather than leaving the moment functions $\boldsymbol{g}_i^{u,p}(x_i,\cdot)$ in the optimization problem.

In most applications, the distribution $\tilde{\eta}(\cdot|x_i)$ may be taken to be proportional to a normal distribution:

$$d\tilde{\eta}(\cdot|x_i) \propto \exp(-||\boldsymbol{g}_i^{m,\omega}(x_i,e_i)||^2),$$

where the value of the mean and variance are inconsequential for the validity of the result. To draw from this distribution, the first step is to obtain latent variables that satisfy the moment functions $\boldsymbol{g}_i^{u,p}(x_i,e_i)$ and can be achieved by rejection sampling. Then, a standard Metropolis-Hastings algorithm can be used to draw from the distribution.[24]

5.3 Statistical Testing

The notion of PS-rationalizability together with Theorem 2 provides a feasible way of checking whether the data are consistent with the model. To statistically test the PS-rationalizability of a data set, let

$$\hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma}) := \frac{1}{N}\sum_{i=1}^{N}\tilde{\boldsymbol{h}}_i(x_i,\boldsymbol{\gamma})$$

and

$$\hat{\tilde{\boldsymbol{\Omega}}}(\boldsymbol{\gamma}) := \frac{1}{N}\sum_{i=1}^{N}\tilde{\boldsymbol{h}}_i(x_i,\boldsymbol{\gamma})\tilde{\boldsymbol{h}}_i(x_i,\boldsymbol{\gamma})' - \hat{\tilde{\boldsymbol{h}}}_i(\boldsymbol{\gamma})\hat{\tilde{\boldsymbol{h}}}_i(\boldsymbol{\gamma})'$$

denote the sample analogues of $\tilde{\boldsymbol{h}}$ and its variance, respectively. Furthermore, let $\hat{\tilde{\boldsymbol{\Omega}}}^-$ denote the generalized inverse of the matrix $\hat{\tilde{\boldsymbol{\Omega}}}$. Schennach (2014) shows that the test statistic

$$\mathrm{TS}_N := N \inf_{\boldsymbol{\gamma}\in\mathbb{R}^{L\cdot T+T}} \hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma})'\hat{\tilde{\boldsymbol{\Omega}}}^-(\boldsymbol{\gamma})\hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma})$$

is stochastically bounded by a χ^2 distribution with $d_m := L \cdot T + T$ degrees of

[24] Additional details about the implementation are given in Appendix A4.

freedom ($\chi^2_{d_m}$).[25] As such, the PS-rationalizability of a data set can be checked by comparing the value of the test statistic against the critical value of the chi-square distribution with d_m degrees of freedom.

5.4 Causal Inference

Conditional on the data being consistent with PS-rationalizability, the next step is to make inference on parameters of interest. First, the next result shows that causal inference is possible in the model.

Proposition 3. *The average expected elasticity of average price with respect to shopping intensity is given by*

$$\frac{1}{L}\sum_{l=1}^{L}\mathbb{E}\left[\frac{\partial\overline{\log(p_t^*)}}{\partial\log(a_{l,t})}\right] = \frac{1}{L}\mathbb{E}\left[\bar{\alpha}^1\right],$$

where $\overline{\log(p_t^*)}$ *is the true average log price across goods and* $\bar{\alpha}^1$ *is the average elasticity of price with respect to shopping intensity.*

Proposition 3 states that the causal effect of the average increase in shopping intensity on the expected average price can be recovered. The reason why causality can be achieved in the model is that Assumption 4 restricts the expected average search ability to be time-invariant. Therefore, any variation in the expected average price must be caused by a variation in shopping intensity.

In the statistical framework previously outlined, inference can be made by adding a moment on a parameter of interest. Proposition 3 suggests to choose the following moment:

$$L^{-1}\mathbb{E}[\bar{\alpha}^1] = \theta_0,$$

where $\bar{\alpha}^1$ is the average elasticity of price with respect to shopping intensity and $\theta_0 \in [-0.25, 0]$ is the average expected elasticity of average price with respect to shopping intensity. As before, this condition can be encapsulated in a moment function:

$$g_i^{\alpha}(x_i, e_i) := L^{-1}\bar{\alpha}_i^1 - \theta_0.$$

A conservative 95% confidence set on θ_0 can be obtained by inverting the test statistic:

$$\{\theta_0 \in \Theta : \mathrm{TS}_N(\theta_0) \le \chi^2_{d_m+1,0.95}\},$$

[25] Aguiar and Kashaev (2018) further show that the test has an asymptotic power equal to one.

where $TS_N(\theta_0)$ is the test statistic at a fixed value of θ_0.

6 Empirical Application

In this section, I check whether the data are PS-rationalizable, set estimate the shopping technology across multiple demographics, relates price search to consumption inequality, and test the validity of instrumental variables.

6.1 Price Search

By applying the above methodology to my sample, I find that the data do not reject PS-rationalizability at the 95% confidence level. More precisely, I obtain a test statistic of 36.38, which is below the chi-square critical value of 43.77. In contrast, I find that PS-rationalizability is rejected by the data in couple households as the test statistic is 392.56.

Since the model is not rejected by the data on consumers, I can invert the statistical test to obtain a 95% confidence set on the average expected elasticity of average price with respect to shopping intensity. The results for all consumers, low-income consumers, and high-income consumers are reported in Figure 5.

There, we see that the average expected elasticity of average price with respect to shopping intensity is about -0.1925. That is, doubling shopping intensity decreases the average price paid by about 19.25% for both income groups on average. If differences in prices paid are not due to heterogeneity in the shopping technology, a possible explanation is that low-income consumers shop more intensively than high-income consumers. To investigate this prospect, Figure 6 displays the log number of shopping trips by income group.

Figure 6 shows that shopping intensity is almost identical between income groups. Overall, consumers earning less than $\$25,000$ a year are only making 1.65% more shopping trips per month than consumers earning more than $\$50,000$ a year.

To investigate whether there is heterogeneity across other dimensions, I set estimate the shopping technology by gender, education, geographic location, and occupation. Gender separates the sample between males and females, education between consumers that did not graduate college and those that graduated college, geographic location between consumers in rural states and those in urban states, and occupation between workers and retirees.[26]

[26] A rural state is defined as one with an urban population as a percentage of total population below that of the U.S. population, and an urban state as one with an urban population as a

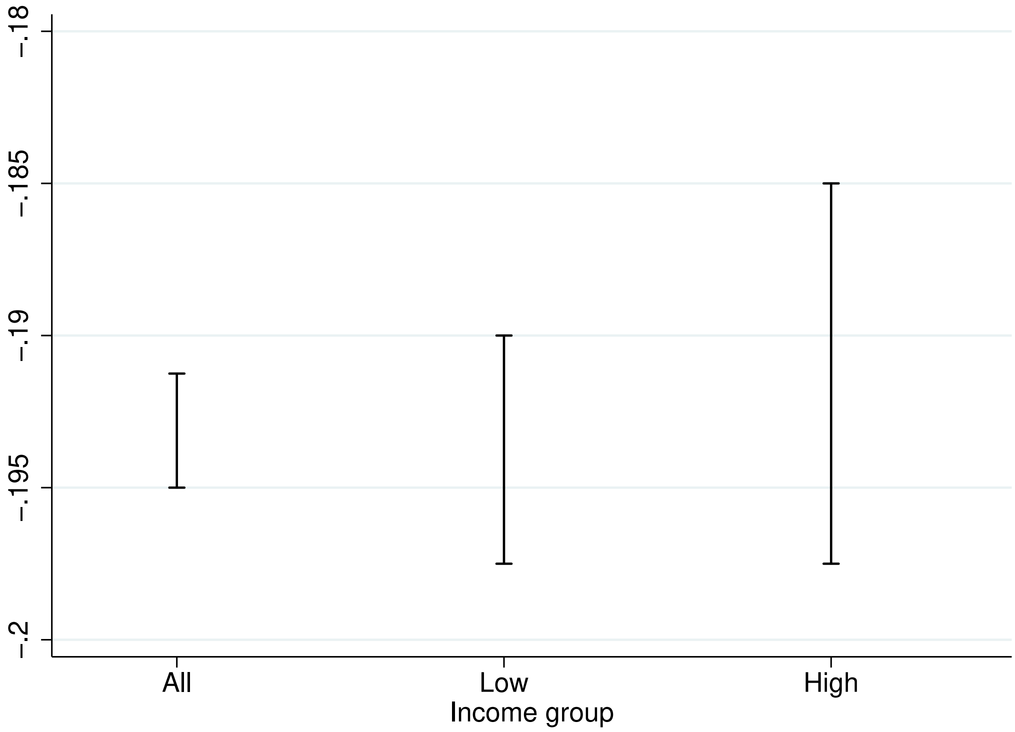

Figure 5: Average Expected Elasticity of Average Price with Respect to Shopping Intensity ($\mathbb{E}[\bar{\alpha}]$)

Notes: The vertical axis represents the average expected elasticity of average price with respect to shopping intensity. Low-income consumers are defined as those with an income lower than $25,000. High-income consumers are defined as those with an income greater than $50,000. The sample size is 1645 for all, 660 for low-income consumers, and 348 for high-income consumers.

For every demographic, the 95% confidence set is $[-0.1975, -0.19]$, with the exception of workers where the confidence set is $[-0.195, -0.19]$.[27] Since the model allows for sizable heterogeneity, the confidence sets on the elasticity reflect inherent homogeneity in the average shopping technology rather than induced homogeneity through ex ante restrictions.

6.2 Consumption Inequality

The previous subsection showed that the average shopping technology is mostly homogeneous across income groups. Moreover, Figure 6 showed that income groups have comparable shopping intensities. Therefore, heterogeneity in price search does not explain the difference in prices paid between low- and high-

percentage of total population above that of the U.S. population.

[27] The 95% confidence set is identical across those demographics at a precision level of 0.0025. Therefore, any difference in the confidence set must be by less than 0.005.

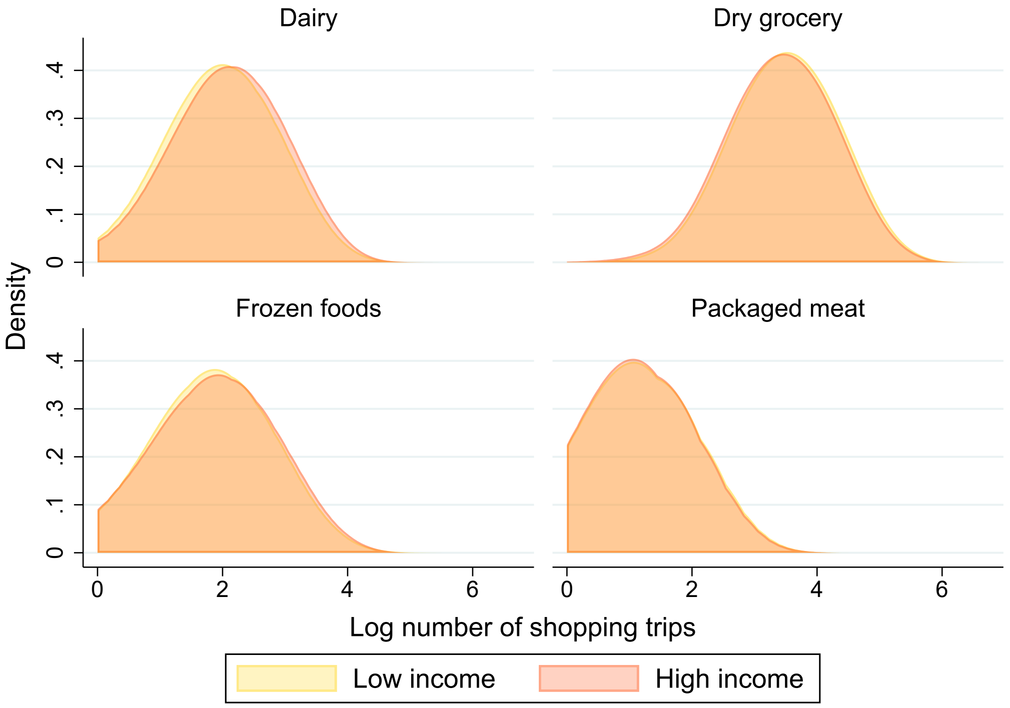

Figure 6: Log Number of Shopping Trips Density by Department Category

Notes: Low-income consumers are defined as those with an income lower than \$25,000. High-income consumers are defined as those with an income greater than \$50,000. The sample size is 660 for low-income consumers and 348 for high-income consumers.

income consumers depicted in Figure 3.

Since low-income consumers tend to pay lower prices, they may still be able to achieve a similar consumption level to high-income consumers despite their lower income. To assess the extent of consumption inequality in the data, Figure 7 compares the distribution of log consumption between low- and high-income consumers.

Figure 7 shows that consumption is close to identical across income groups. Precisely, low-income consumers only have a 0.43% lower consumption level per month compared to high-income consumers. Combined with the finding that price search is homogeneous, my results suggest that low-income consumers mainly increase their consumption level by purchasing goods of lower quality rather than through price search.

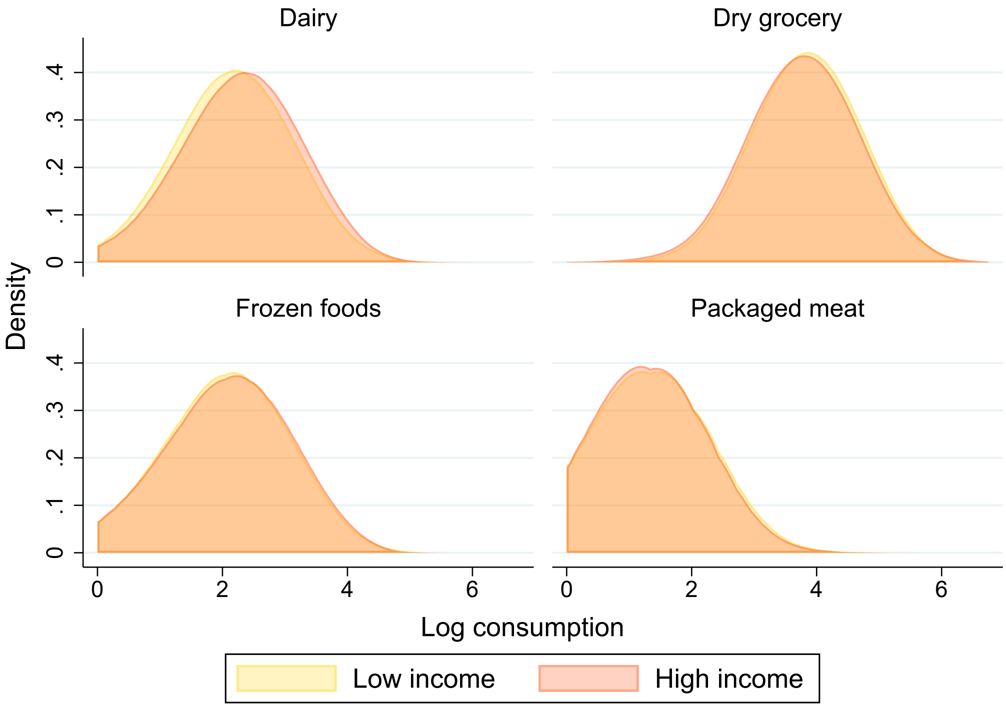

Figure 7: Log Consumption Density by Department Category

Notes: Consumption represents the number of UPCs purchased. Low-income consumers are defined as those with an income lower than $\$25,000$. High-income consumers are defined as those with an income greater than $\$50,000$. The sample size is 660 for low-income consumers and 348 for high-income consumers.

6.3 Instrumental Variable

The statistical framework allows me to impose additional moments to test the validity of an instrument. For conciseness, I consider the validity of income as it is the main instrument used in Aguiar and Hurst (2007). Income is a valid instrument if the exogeneity assumption $\mathbb{E}[y_t \omega_{l,t}] = 0$ holds for all $l \in L$ and $t \in T$. To limit the dimensionality of the problem, I only impose those moments at $t = 1$. Testing the model with this additional restriction brings the total number of moments to 34 and yields a test statistic of 80.12. Since this value is above the chi-square critical value of 48.60, instrumental variable is rejected in my data set.[28] Moreover, income would also need to satisfy $\mathbb{E}[y_t m_{l,t}] = 0$ to be valid if measurement error in prices is additive. The model is rejected with a test statistic of 113.69 when further imposing this set of moments.

[28] This result does not directly translate into the rejection of income in Aguiar and Hurst (2007) because the aggregation of their data set is different from mine.

6.4 Discussion

Price search allows consumers to pay prices that depend on their own shopping intensity. The resulting heterogeneity in prices paid means that expenditure may give an erroneous account of consumption and, hence, consumption inequality. In a calibrated model of price search, Arslan et al. (2021) show that consumption inequality is significantly smaller than expenditure inequality in the Homescan 2004. Consistent with their finding, Figure 3 and Figure 7 display disparity in prices paid despite similar consumption levels between income groups. The difference in expenditures is attributable to lower prices paid by low-income consumers. As such, an analysis based on expenditures would overstate actual consumption inequality in the data.

The conclusion that consumption inequality is negligible between income groups appears somewhat counterintuitive, especially given the overwhelming evidence that consumption inequality has increased over time such as in Aguiar and Bils (2015).[29] This finding can be reconciled by two observations. First, Aguiar and Bils (2015) measure the change in consumption inequality by comparing relative expenditures on luxury versus necessity goods. Since my data set only contains food categories (necessities), the rise in consumption inequality can be explained by changes in expenditures on luxury goods. Second, consumption inequality is typically measured from data on expenditures, thus ignoring differences in prices paid between income groups. As discussed previously, this can lead to an inflated measure of consumption inequality.

My application shows that price search has a strong impact on average prices paid. Furthermore, Figure 5 shows that low- and high-income consumers have an essentially identical shopping technology. Thus, most of the price differentials between income groups displayed in Figure 3 are due to differences in good quality. Using data from the National Health and Nutrition Examination Survey, Wang et al. (2014) document an increase in diet quality inequality between socioeconomic groups.[30] To the extent that lower quality goods are also less healthy, consumption inequality between income groups likely takes the form of diet quality inequality.

[29] See Attanasio and Pistaferri (2016) for a review of the literature investigating the evolution of consumption inequality.

[30] Individuals with low socioeconomic status are defined as those with less than 12 years of education and an income below 130% of the poverty line. Individuals with high socioeconomic status are defined as those with more than 12 years of education and an income above 350% above the poverty line.

7 Conclusion

This paper proposes a model of price search that is shown to be consistent with the Nielsen Homescan data. Using aggregated data on food expenditures, I obtain a robust confidence set on the causal effect of an average increase in shopping intensity on the average price paid. I find that the average shopping technology is homogeneous across demographics. Furthermore, I document that low-income consumers pay lower prices compared to high-income consumers and that both income groups have comparable consumption levels. Therefore, my results suggest that the observed price differential is mostly attributable to differences in the quality of goods purchased.

To the best of my knowledge, this paper is the first to use the methodology of Schennach (2014) to statistically test a large-scale structural model and make inference on structural parameters. The ability to test for the consistency of a data set with the model improves upon the standard approach of finding the set of parameters that minimizes the norm of the moments defining the model. Since the sanity of the model can be checked, the sanity of the estimated parameters is guaranteed. In my model, I further show that the set estimates of the shopping technology are causal.

The framework I use may be complementary to the estimation strategy of gross production functions by Gandhi et al. (2020) to models where point-identification does not obtain. The methodology can be applied using the concavity of the production function and some centering condition on the aggregate productivity across firms. This could be useful to relax the Markov assumption on productivity and assess the sensitivity of existing results to this restriction. The implementation could require firms to know the ex post productivity shock or some information about its structure.

Appendix

A1: Relationship with Models of Household Production

Although the focus of this paper is on the price function, the framework of the model is consistent with one of household production similar in spirit to that of Becker (1965). As an illustration, I extend my model to one of household production and shows that it has close ties with that of Aguiar and Hurst (2007). For ease of comparison, I consider the static version of my model.

Suppose that, in addition to spending time shopping, the household can spend time in home production denoted by $h \in \mathbb{R}_{++}$. By using that time input along with market goods, the household can produce some homemade good K by using its (concave) home production function $f(h, \boldsymbol{c})$.[31] The household's problem therefore becomes

$$\max_{(\boldsymbol{c},\boldsymbol{a},K,h)\in C\times A\times\mathbb{R}^2_{++}} u(\boldsymbol{a}, K, h) \;\; s.t. \;\; \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)'\mathbf{c} = y_t$$
$$f(\boldsymbol{c}, h) = K.$$

One can get rid of the second constraint by substituting it for K in the utility function, yielding

$$\max_{(\boldsymbol{c},\boldsymbol{a},h)\in C\times A\times\mathbb{R}_{++}} u(\boldsymbol{a}, f(\boldsymbol{c}, h), h) \;\; s.t. \;\; \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)'\mathbf{c} = y_t.$$

Assuming the opportunity cost of time is additively separable, linear, and identical for the shopper and the home producer, the problem boils down to

$$\max_{(\boldsymbol{c},\boldsymbol{a},h)\in C\times A\times\mathbb{R}_{++}} u(f(\boldsymbol{c}, h)) + \boldsymbol{\mu}_t'\boldsymbol{a} + \mu_t h \;\; s.t. \;\; \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)'\mathbf{c} = y_t,$$

where μ_t denotes the disutility from the time spent on either activity. Since both $u(\cdot)$ and $f(\cdot,\cdot)$ are unobservable concave functions, this maximization problem is observationally equivalent to

$$\max_{(\boldsymbol{c},\boldsymbol{a},h)\in C\times A\times\mathbb{R}_{++}} f(\boldsymbol{c}, h) + \boldsymbol{\mu}_t'\boldsymbol{a} + \mu_t h \;\; s.t. \;\; \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)'\mathbf{c} = y_t,$$

and we have thereby recovered a model with the same implications to that of Aguiar and Hurst (2007).[32] To see why, assume the solution is interior and take the first-order conditions:

$$\frac{\partial f}{\partial c} = \lambda_t \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)$$
$$\boldsymbol{\mu} = \lambda_t \frac{\partial \boldsymbol{p}(\boldsymbol{a}, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}} \odot \boldsymbol{c}$$
$$\mu = -\frac{\partial f}{\partial h}.$$

[31] One can think of market goods as comestible such as eggs, sugar and pecans. By spending h unit of time cooking, the household can transform these "raw goods" into a pecan pie, the final good consumed by the household.

[32] Despite that the two maximization problems are observationally equivalent, eliminating the utility function changes the interpretation of the model.

It follows that the marginal rate of transformation (MRT) between time and goods in shopping equals the MRT in home production:

$$\frac{\partial f}{\partial h} / \frac{\partial f}{\partial c_l} = -\frac{\frac{\partial p_l(a_l, \omega_{l,t})}{\partial a_l} \cdot c_l}{p_l(a_l, \omega_{l,t})} \quad \forall l \in L.$$

This derivation shows that the household production version of my model naturally extends that of Aguiar and Hurst (2007). Conditional on knowing the price function, this last equation can be used to identify the home production function, a point that was cleverly exploited by Aguiar and Hurst (2007) in a parametric setting. Note that using exponential discounting as defined in (1) would yield $\lambda_t \delta^{-t}$ instead of λ_t in the first-order conditions and leave the MRT unchanged.

A2: Sample Construction

The Homescan contains information on purchases made by U.S. households in a wide variety of retail outlets. After every trip to a retail outlet, information about the trip is recorded by the panelist via a scanner device. Each trip may have one or many UPC purchases. In total, there are $66,321,848$ purchases in the panel year 2011. Among them, $43,432,246$ pertain to the departments of dry grocery, frozen foods, dairy and packaged meat. Since some purchases in the panel year are outside of the calendar year 2011, I remove them from the sample. This operation drops $751,479$ purchases, leaving a total of $42,680,767$ purchases.

For each household-month, I average UPC prices across trips. Precisely, for any household $i \in N$ and month $t \in T$, the weighted average price for a given UPC is given by

$$\bar{p}_{i,UPC,t} = \frac{\sum_{trips_i \in t} p_{i,UPC,trips_i} c_{i,UPC,trips_i}}{\sum_{trips_i \in t} c_{i,UPC,trips_i}},$$

where $trips_i$ denotes a trip of household i. This aggregation is only computed for UPCs that are purchased by a given household in a given month.

The Homescan has a total of $4,510,908$ distinct UPCs, with $1,633,850$ that belong to the four departments considered: dry grocery, frozen foods, dairy, and packaged meat. To keep the analysis tractable and mitigate stockpiling issues, I aggregate UPCs to their department categories. For each household-month, the weighted average price for a given department $l \in L$ is given by

$$p_{i,l,t} = \frac{\sum_{UPC \in l} \tilde{p}_{i,UPC,t} c_{i,UPC,t}}{\sum_{UPC \in l} c_{i,UPC,t}}.$$

Furthermore, I only keep data from April to September. The main reason for limiting the number of goods and time periods is to control the computational burden. Since the number of parameters to solve for in the model is given by $L \cdot T + T$, the nonlinear optimization problem becomes quickly intractable when either L or T increases.

As the methodology requires the data to be strictly positive, I drop households that do not meet this requirement for any aggregated good and month. These conditions bring down the number of households from $62,092$ to $16,025$. Further limiting the sample to single households that are at least 50 years old decreases the number of households to 1668. Finally, I drop households that have zero prices paid, thus decreasing the sample size to 1645.[33]

I restrict the sample to single households to avoid the false rejection of the model. As Adams et al. (2014) point out, inconsistencies may arise due to negotiation within a couple household. Jackson and Yariv (2015) further show that time inconsistent behavior will appear if individuals in a non-dictatorial household have different discount factors. By accounting for measurement error in survey data, Aguiar and Kashaev (2018) show that single households behave consistently with exponential discounting while couple households do not.

A3: Power Analysis

In this section, I show that price search and utility maximization are both refutable under Assumptions 1-5. I then provide empirical evidence that these additional restrictions are not necessary for the model to be rejected by the data.

Convexity of the Log-linear Shopping Technology

Let the price function for any good $l \in L$ have the log-linear shopping technology specified by Assumption 1:

$$\log(p_{l,t}(a_{l,t}, \omega_{l,t})) = \alpha_l^0 + \alpha_l^1 \log(a_{l,t}) - \omega_{l,t}.$$

[33] Zero prices may arise because of "free-good" promotions or if the household enters a price equal to zero and no historical information regarding a valid price for the UPC is available.

It is easy to see that, for any $l \in L$, the Hessian of the log price function is

$$H(a_{l,t}, \omega_{l,t}) = \begin{bmatrix} -\frac{\alpha_l^1}{a_{l,t}^2} & 0 \\ 0 & 0 \end{bmatrix}.$$

The principal minors are $D_1 = -\frac{\alpha_l^1}{a_{l,t}^2} \geq 0$, $D_2 = 0$, and $D_3 = 0$. Accordingly, the log price functions are convex and, therefore, the price functions logarithmically convex.[34]

Falsifiability of Price Search

Suppose that Assumptions 1-5 are satisfied and let $L = 2$, $T = 2$. Let observed prices be such that $\boldsymbol{p}_1 = [1, 2]'$, $\boldsymbol{p}_2 = [3, 4]'$ almost surely, shopping intensity be such that $\boldsymbol{a}_1 = [1, 2]'$, $\boldsymbol{a}_2 = [2, 3]'$, and consumption be such that $\boldsymbol{c}_t > 0$ for $t = 1, 2$.

Convexity of the log price functions implies that for all $l \in L$ and $s, t \in T$, we have

$$\log\left(\frac{p(a_{l,s}, \omega_{l,s})}{p(a_{l,t}, \omega_{l,t})}\right) \geq \frac{\nabla_a p(a_{l,t}, \omega_{l,t})}{p(a_{l,t}, \omega_{l,t})}(a_{l,s} - a_{l,t}) + \frac{\nabla_\omega p(a_{l,t}, \omega_{l,t})}{p(a_{l,t}, \omega_{l,t})}(\omega_{l,s} - \omega_{l,t}).$$ [35]

The above expression can be written more concisely as

$$\log\left(\frac{p_{l,s}^*}{p_{l,t}^*}\right) \geq \frac{\rho_{l,t}}{p_{l,t}^* c_{l,t}}(a_{l,s} - a_{l,t}) - (\omega_{l,s} - \omega_{l,t}) \quad \forall s, t \in T.$$

Summing up these inequalities for each good $l \in L$ and dividing by L gives

$$\frac{1}{L}\sum_{l=1}^{L} \log\left(\frac{p_{l,s}^*}{p_{l,t}^*}\right) \geq \frac{1}{L}\sum_{l=1}^{L} \frac{\rho_{l,t}}{p_{l,t}^* c_{l,t}}(a_{l,s} - a_{l,t}) - (\bar{\omega}_s - \bar{\omega}_t) \quad \forall s, t \in T,$$

where $\bar{\omega}_t := \frac{1}{L}\sum_{l=1}^{L} \omega_{l,t}$ for all $t \in T$. Taking the expectation for $s = 1$, $t = 2$ and using the assumption that $\mathbb{E}[\log(\boldsymbol{p}_t)] = \mathbb{E}[\log(\boldsymbol{p}_t^*)]$ for all $t \in T$, we get

$$0 > \frac{1}{L}\sum_{l=1}^{L} \left(\mathbb{E}\left[\log(p_{l,1})\right] - \mathbb{E}\left[\log(p_{l,2})\right]\right) \geq -\mathbb{E}\left[\frac{\rho_{l,2}}{p_{l,2}^* c_{l,2}}\right]. \quad (5)$$

Noting that the random variable on the right-hand side is always negative, it

[34] A function f is logarithmically convex if the composition of the logarithm with f is itself a convex function.

[35] Note that this expression is well-defined since prices are strictly positive.

follows that the negative of its expectation is positive: $-\mathbb{E}\left[\frac{\rho_{l,2}}{p^*_{l,2}c_{l,2}}\right] \geq 0$. Clearly, inequality (5) yields a contradiction. In other words, the data are inconsistent with the model provided the price functions are log-linear.

Falsifiability of Utility Maximization

Suppose that Assumptions 1-5 are satisfied and let $L = 2$, $T = 2$. Let observed prices be such that $\boldsymbol{p}_1 = [1, 2]'$, $\boldsymbol{p}_2 = [3, 4]'$ almost surely, shopping intensity be such that $\boldsymbol{a}_1 = [2, 3]'$, $\boldsymbol{a}_2 = [1, 2]'$, and consumption be such that $\boldsymbol{c}_1 = [1, 1]'$, $\boldsymbol{c}_2 = [2, 2]'$.

Concavity of the utility function implies that for all $s, t \in T$

$$u(\boldsymbol{c}_s, \boldsymbol{a}_s) - u(\boldsymbol{c}_t, \boldsymbol{a}_t) \leq \nabla_c u(\boldsymbol{c}_t, \boldsymbol{a}_t)'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \nabla_a u(\boldsymbol{c}_t, \boldsymbol{a}_t)'(\boldsymbol{a}_s - \boldsymbol{a}_t).$$

Summing up these inequalities for $s = 1$, $t = 2$ and $s = 2$, $t = 1$, we can obtain

$$0 \leq \left[(\boldsymbol{p}^*_2 - \boldsymbol{p}^*_1)'(\boldsymbol{c}_1 - \boldsymbol{c}_2) + (\boldsymbol{\rho}_2 - \boldsymbol{\rho}_1)'(\boldsymbol{a}_1 - \boldsymbol{a}_2)\right],$$

where I assumed that $\delta = 1$ almost surely. For concavity to be refuted, it is clear that Assumption 2 needs to be changed to $\mathbb{E}[\boldsymbol{p}_t] = \mathbb{E}[\boldsymbol{p}^*_t]$ for all $t \in T$. Taking the expectation then yields

$$\begin{aligned}
0 &\leq (\mathbb{E}[\boldsymbol{p}_2] - \mathbb{E}[\boldsymbol{p}_1])'(\boldsymbol{c}_1 - \boldsymbol{c}_2) + (\mathbb{E}[\boldsymbol{\rho}_2] - \mathbb{E}[\boldsymbol{\rho}_1])'(\boldsymbol{a}_1 - \boldsymbol{a}_2) \\
&= -4 + \sum_{l=1}^{L}(\mathbb{E}[\rho_{l,2}] - \mathbb{E}[\rho_{l,1}]) \\
&\leq -4 - \sum_{l=1}^{L}\mathbb{E}[\rho_{l,1}] \\
&\leq -4 + \frac{1}{2} + \frac{2}{3} \\
&< 0,
\end{aligned}$$

where the first equality substituted the expected value of true prices for their expected observed values, the second inequality used the assumption that $\boldsymbol{\rho}_t \leq 0$ for all $t \in T$, and the third inequality exploited the fact that $-\alpha_l \leq 1$ for all $l \in L$, $\boldsymbol{c}_1 = [1, 1]'$ and $\boldsymbol{a}_1 = [2, 3]'$.

Clearly, these inequalities yield a contradiction. As such, utility maximization can be rejected by the data under Assumptions 1-5 provided $\mathbb{E}[\boldsymbol{p}_t] = \mathbb{E}[\boldsymbol{p}^*_t]$ for all $t \in T$ (instead of Assumption 2) and $\delta = 1$ almost surely.

Falsifiability of the Model: Empirical Evidence

I have shown analytically that the model defined by Assumptions 1-5 can be rejected by the data with only two time periods if either (1) the price functions are log-linear, or (2) the discount factor equals one almost surely and measurement error satisfies $\mathbb{E}[\boldsymbol{p}_t] = \mathbb{E}[\boldsymbol{p}_t^*]$ for all $t \in T$.

To complement the above analysis, I now provide empirical evidence that the model can be rejected by the data under Assumptions 2-5 if the price functions are convex decreasing.[36] This corresponds to the fully nonparametric version of the model. To this end, I consider a data set where $\boldsymbol{p}_1 = [1, 2]'$, $\boldsymbol{p}_2 = [3, 4]$, $\boldsymbol{a}_1 = [1, 2]'$, $\boldsymbol{a}_2 = [2, 3]'$, and $\boldsymbol{c}_1 = [1, 4]'$, $\boldsymbol{c}_2 = [3, 2]'$. I let the sample size be 500 where, for simplicity, every consumer is assumed to have the same data set.

The results derived previously do not allow me to conclude that the model has any empirical content without the log-linearity of the price functions. Nevertheless, an application of the methodology to the constructed data set yields a test statistic of 476.98, well-above the chi-square critical value of 12.59.

A4: Implementation

In this section, I provide a pseudo-algorithm of the ELVIS approach proposed by Schennach (2014) specialized to my model. Furthermore, I provide pseudo-algorithms for the construction of the conditional distribution $\tilde{\eta}$ and the integration of the latent variables.

Pseudo-Algorithm

Step 1

- Fix the number of goods L and the number of time periods T.
- Fix the data set $x = (x_i)_{i=1}^N$, where $x_i = (\boldsymbol{p}_{i,t}, \boldsymbol{c}_{i,t}, \boldsymbol{a}_{i,t})_{t \in T}$.
- Fix the moments defining the model: $\boldsymbol{g}_i^u$, $\boldsymbol{g}_i^p$, $\boldsymbol{g}_i^m$, $\boldsymbol{g}^\omega$.
- Fix the support of the structural parameters: $\delta_i \in [0.95, 1]$ and $\boldsymbol{\alpha}_i^1 \in [-1, 0]$.
- Fix the conditional distribution of the latent variables $\tilde{\eta}$.

Step 2

[36] Formally, a function $f : \mathbb{R}^L \to \mathbb{R}$ is convex if and only if $f(\boldsymbol{x}) \geq f(\boldsymbol{y}) + \nabla_y' f(\boldsymbol{y})(\boldsymbol{x} - \boldsymbol{y})$ for all $\boldsymbol{x}, \boldsymbol{y} \in \mathbb{R}^L$. It is convex decreasing if it is convex and $\nabla f(\boldsymbol{y}) \leq 0$ for all $\boldsymbol{y}$.

for $i = 1 : N$

- Integrate the latent variables under $\tilde{\eta}(\cdot|x_i)$ to obtain $\tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma})$.

end

- Compute $\hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma}) = \frac{1}{N}\sum_{i=1}^{N} \tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma})$.
- Compute $\hat{\tilde{\boldsymbol{\Omega}}}(\boldsymbol{\gamma}) = \frac{1}{N}\sum_{i=1}^{N} \tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma})\tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma})' - \hat{\tilde{\boldsymbol{h}}}_i(\boldsymbol{\gamma})\hat{\tilde{\boldsymbol{h}}}_i(\boldsymbol{\gamma})'$.
- Compute the objective function: $\mathrm{ObjFct}(\boldsymbol{\gamma}) = N\hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma})'\hat{\tilde{\boldsymbol{\Omega}}}(\boldsymbol{\gamma})^{-}\hat{\tilde{\boldsymbol{h}}}(\boldsymbol{\gamma})$.

Step 3

- Compute $\mathrm{TS}_N = \min_{\boldsymbol{\gamma}} \mathrm{ObjFct}(\boldsymbol{\gamma})$.

Step 1 (Construction of $\tilde{\eta}$)
The distribution $\tilde{\eta}$ can be taken to be proportional to a normal distribution:

$$d\tilde{\eta}(\cdot|x_i) \propto \exp(-||\boldsymbol{g}_i^{m,\omega}(x_i, e_i)||^2),$$

where $\boldsymbol{g}_i^{m,\omega}$ is the set of moments on measurement error and search ability. The following pseudo-algorithm details how to construct the conditional distribution by using rejection sampling and applying Metropolis-Hastings on each passing draw. I draw true prices instead of measurement error as it ensures true prices to be strictly positive. Let $R > 0$.

while $r \leq R$

- Draw candidate latent variables $e_i^c = (\delta_i, \boldsymbol{p}_{i,t}^*, \boldsymbol{\alpha}_i^1, \boldsymbol{\omega}_{i,t})_{t\in T}$ such that their support constraints are satisfied.
- Given x_i and e_i^c, check whether the model is satisfied by using Proposition 1. If the model is not satisfied, go a step back.
- Draw ζ from $U[0, 1]$
- If $-\left(||\boldsymbol{g}_i^{m,\omega}(x_i, e_i^c)||^2 - ||\boldsymbol{g}_i^{m,\omega}(x_i, e_i^{r-1})||^2\right) > \log(\zeta)$, set e_i^r to e_i^c. Else, set e_i^r to e_i^{r-1}.
- Set $r = r + 1$

end

Step 2 (Latent Variable Integration)

- Fix x_i, $\tilde{\eta}$, and $\boldsymbol{\gamma}$.
- Set $\tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma}) = 0$

while $r \leq R$

- Draw e_i^c proportional to $\tilde{\eta}(\cdot|x_i)$.
- Draw ζ from $U[0,1]$
- If $\left[\boldsymbol{g}_i^{m,\omega}(x_i, e_i^c) - \boldsymbol{g}_i^{m,\omega}(x_i, e_i^{r-1})\right]' \boldsymbol{\gamma} > \log(\zeta)$, set e_i^r to e_i^c. Else, set e_i^r to e_i^{r-1}.
- Compute $\tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma}) = \tilde{\boldsymbol{h}}_i(x_i, \boldsymbol{\gamma}) + \boldsymbol{g}_i^{m,\omega}(x_i, e_i^r)/R$
- Set $r = r + 1$

end

A5: Proofs

To reduce the notational burden, I remove the subscript i from the variables in the rest of this section.

Proof of Theorem 1
$(i) \implies (ii)$
Suppose the data have been generated by (1) where the utility function is continuous, concave, strictly increasing in consumption and decreasing in shopping intensity. Then, the first-order conditions of the consumer's problem are given by

$$\nabla_c u(\boldsymbol{c}_t, \boldsymbol{a}_t) = \lambda_t \delta^{-t} \boldsymbol{p}_t,$$
$$\nabla_a u(\boldsymbol{c}_t, \boldsymbol{a}_t) = \lambda_t \delta^{-t} \frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t.$$

Since the utility function is assumed strictly increasing in consumption, it must be that $\nabla_c u(\boldsymbol{c}, \boldsymbol{a}) = \lambda_t \delta^{-t} \boldsymbol{p}_t > 0$. Accordingly, it follows that $\boldsymbol{p}_t > 0$. Likewise, the assumption that the utility function is decreasing in shopping intensity entails

$\nabla_a u(\boldsymbol{c}_t, \boldsymbol{a}_t) = \lambda_t \delta^{-t} \frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \leq 0$ and, hence, $\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \leq 0$. Finally, concavity of the utility function implies

$$u(\boldsymbol{c}_s, \boldsymbol{a}_s) - u(\boldsymbol{c}_t, \boldsymbol{a}_t) \leq \nabla_c u(\boldsymbol{c}_t, \boldsymbol{a}_t)'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \nabla_a u(\boldsymbol{c}_t, \boldsymbol{a}_t)'(\boldsymbol{a}_s - \boldsymbol{a}_t) \quad \forall s, t \in T.$$

Combining the first-order conditions with concavity of the utility function and letting $u_t := u(\boldsymbol{c}_t, \boldsymbol{a}_t)$ for all $t \in T$ yields

$$u_s - u_t \leq \lambda_t \delta^{-t} \left[\boldsymbol{p}_t'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a}_s - \boldsymbol{a}_t) \right] \quad \forall s, t \in T,$$

as desired.

$(ii) \implies (i)$
Starting from the first set of inequalities in Theorem 1 (ii), we have

$$u_s \leq u_t + \lambda_t \delta^{-t} \left[\boldsymbol{p}_t'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a}_s - \boldsymbol{a}_t) \right] \quad \forall s, t \in T.$$

Fix some $t \in T$ and let $t_1 := t$. Consider any sequence of finite indices $\tau = \{t_i\}_{i=1}^m$, $m \geq 2$, $t_i \in T$. Let $\mathcal{I}$ be the set of all such indices and define

$$u(\boldsymbol{c}, \boldsymbol{a}) = \min_{\tau \in \mathcal{I}} \left\{ \lambda_{t_m} \delta^{-t_m} \left[\boldsymbol{p}_{t_m}' (\boldsymbol{c} - \boldsymbol{c}_{t_m}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_m}, \boldsymbol{\omega}_{t_m})}{\partial \boldsymbol{a}_{t_m}} \odot \boldsymbol{c}_{t_m} \right)' (\boldsymbol{a} - \boldsymbol{a}_{t_m}) \right] \right.$$
$$\left. + \sum_{i=1}^{m-1} \lambda_{t_i} \delta^{-t_i} \left[\boldsymbol{p}_{t_i}' (\boldsymbol{c}_{t_{i+1}} - \boldsymbol{c}_{t_i}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_i}, \boldsymbol{\omega}_{t_i})}{\partial \boldsymbol{a}_{t_i}} \odot \boldsymbol{c}_{t_i} \right)' (\boldsymbol{a}_{t_{i+1}} - \boldsymbol{a}_{t_i}) \right] \right\}.$$

This function is the pointwise minimum of a collection of linear functions. As such, $u(\boldsymbol{c}, \boldsymbol{a})$ is concave and continuous. Moreover, the second set of inequalities in Theorem 1 (ii) guarantees that the utility function is strictly increasing in consumption. Likewise, the third set of inequalities implies that it is decreasing in shopping intensity.

If the budget sets $\{\mathcal{B}_t\}_{t=1}^T$ are convex, then the first-order conditions of the model are necessary and sufficient for a maximum. Therefore, I am left to show that $\lambda_t \delta^{-t} \boldsymbol{p}_t \in \nabla_c u(\boldsymbol{c}_t, \boldsymbol{a}_t)$ and $\lambda_t \delta^{-t} \frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \in \nabla_a u(\boldsymbol{c}_t, \boldsymbol{a}_t)$ for all $t \in T$.

Let $\epsilon > 0$, $t \in T$, and note that by definition of $u(\cdot, \cdot)$, there is some sequence of indices $\tau \in \mathcal{I}$ such that

$$u(\boldsymbol{c}_t, \boldsymbol{a}_t) + \epsilon > \lambda_{t_m} \delta^{-t_m} \left[\boldsymbol{p}'_{t_m} (\boldsymbol{c}_t - \boldsymbol{c}_{t_m}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_m}, \boldsymbol{\omega}_{t_m})}{\partial \boldsymbol{a}_{t_m}} \odot \boldsymbol{c}_{t_m} \right)' (\boldsymbol{a}_t - \boldsymbol{a}_{t_m}) \right]$$
$$+ \sum_{i=1}^{m-1} \lambda_{t_i} \delta^{-t_i} \left[\boldsymbol{p}'_{t_i} (\boldsymbol{c}_{t_{i+1}} - \boldsymbol{c}_{t_i}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_i}, \boldsymbol{\omega}_{t_i})}{\partial \boldsymbol{a}_{t_i}} \odot \boldsymbol{c}_{t_i} \right)' (\boldsymbol{a}_{t_{i+1}} - \boldsymbol{a}_{t_i}) \right]$$
$$\geq u(\boldsymbol{c}_t, \boldsymbol{a}_t).$$

Add any bundle $(\boldsymbol{c}, \boldsymbol{a}) \in C \times A$ to the sequence and use the definition of $u(\cdot, \cdot)$ once again to obtain

$$\lambda_{t_m} \delta^{-t_m} \left[\boldsymbol{p}'_{t_m} (\boldsymbol{c}_t - \boldsymbol{c}_{t_m}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_m}, \boldsymbol{\omega}_{t_m})}{\partial \boldsymbol{a}_{t_m}} \odot \boldsymbol{c}_{t_m} \right)' (\boldsymbol{a}_t - \boldsymbol{a}_{t_m}) \right]$$
$$+ \sum_{i=1}^{m-1} \lambda_{t_i} \delta^{-t_i} \left[\boldsymbol{p}'_{t_i} (\boldsymbol{c}_{t_{i+1}} - \boldsymbol{c}_{t_i}) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_{t_i}, \boldsymbol{\omega}_{t_i})}{\partial \boldsymbol{a}_{t_i}} \odot \boldsymbol{c}_{t_i} \right)' (\boldsymbol{a}_{t_{i+1}} - \boldsymbol{a}_{t_i}) \right]$$
$$+ \lambda_t \delta^{-t} \left[\boldsymbol{p}'_t (\boldsymbol{c} - \boldsymbol{c}_t) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a} - \boldsymbol{a}_t) \right]$$
$$\geq u(\boldsymbol{c}, \boldsymbol{a}).$$

Hence,

$$u(\boldsymbol{c}_t, \boldsymbol{a}_t) + \epsilon + \lambda_t \delta^{-t} \left[\boldsymbol{p}'_t (\boldsymbol{c} - \boldsymbol{c}_t) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a} - \boldsymbol{a}_t) \right] > u(\boldsymbol{c}, \boldsymbol{a}).$$

Since $\epsilon > 0$, $t \in T$ and $(\boldsymbol{c}, \boldsymbol{a})$ were arbitrary, we get

$$u(\boldsymbol{c}_t, \boldsymbol{a}_t) + \lambda_t \delta^{-t} \left[\boldsymbol{p}'_t (\boldsymbol{c} - \boldsymbol{c}_t) + \left(\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a} - \boldsymbol{a}_t) \right] \geq u(\boldsymbol{c}, \boldsymbol{a}).$$

This corresponds to the definition of concavity and, therefore, it must be that $\lambda_t \delta^{-t} \boldsymbol{p}_t$ and $\lambda_t \delta^{-t} \frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t$ are supergradients of $u(\boldsymbol{c}_t, \boldsymbol{a}_t)$. Next, I show that we can construct a utility function that guarantees the solution to exist.

Let $\Gamma := \max_{l \in L, t \in T} \{a_{l,t}\}$. For every $l \in L$, let and $h_l(\cdot)$ be a continuously differentiable function satisfying $h_l(0) = 0$, $h'_l(x) > 0$, $h''_l(x) \geq 0$ for $x \in \mathbb{R}_+$ and $\lim_{x \to \infty} h'_l(x) = \infty$.[37] To see that there exists a utility function such that a solution exists, define $\hat{u}(\boldsymbol{c}, \boldsymbol{a}) := u(\boldsymbol{c}, \boldsymbol{a}) - \sum_{l=1}^{L} h_l (\max\{0, a_l - \Gamma\})$. As before, this function is concave, continuous, strictly increasing in consumption, and decreasing in shopping intensity. Furthermore, note that $\hat{u}(\boldsymbol{c}, \boldsymbol{a}) \leq u(\boldsymbol{c}, \boldsymbol{a})$ for all $(\boldsymbol{c}, \boldsymbol{a}) \in C \times A$ and $\hat{u}(\boldsymbol{c}_t, \boldsymbol{a}_t) = u(\boldsymbol{c}_t, \boldsymbol{a}_t)$ for all $t \in T$. Thus, $(\boldsymbol{c}_t, \boldsymbol{a}_t)_{t \in T}$ is still a

[37] This construction is analogous to that of Deb et al. (2018).

solution to the consumer problem. Finally, note that $\hat{u}(\boldsymbol{c}, \boldsymbol{a}) \to -\infty$ whenever $\boldsymbol{a} \to \infty$ along some dimension. This follows from the piecewise linearity of $u(\cdot, \cdot)$ and the assumption that $\lim_{x\to\infty} h_l'(x) = \infty$.

Proof of Proposition 1

Suppose the existence of u_t, $\lambda_t > 0$ and $\delta \in [0.95, 1.0]$, such that for all $s, t \in T$, the inequalities in Theorem 1 (ii) hold. The known derivative $\frac{\partial \boldsymbol{p}(\boldsymbol{a}_t, \boldsymbol{\omega}_t)}{\partial \boldsymbol{a}_t} \odot \boldsymbol{c}_t$ directly identifies α_l^0, α_l^1 and $\omega_{l,t}$ in Proposition 1. For the reverse, suppose the existence of u_t, $\lambda_t > 0$, α_l^0, $\alpha_l^1 \leq 0$, $\omega_{l,t}$ and $\delta \in [0.95, 1.0]$, such that for all $l \in L$ and $s, t \in T$, the inequalities in Proposition 1 hold. Note that by Assumption 1, we have

$$\log(p_{l,t}) = \alpha_l^0 + \alpha_l^1 \log(a_{l,t}) - \omega_{l,t}.$$

A solution to Theorem 1 *(ii)* is obtained by letting $\omega_{l,t} := \alpha_l^0 + \alpha_l^1 \log(a_{l,t}) - \log(p_{l,t})$.

Proof of Proposition 2

Fix $(\lambda_t)_{t\in T} \in \mathbb{R}^T_{++}$ and $\delta \in [0.95, 1.0]$. For any $l \in L$, note that the price function equation

$$p_{l,t} = a_{l,t}^{\alpha_l^1} e^{-(\omega_{l,t} - \alpha_l^0)}$$

allows us to express the exponential function as

$$e^{-(\omega_{l,t} - \alpha_l^0)} = \frac{p_{l,t}}{a_{l,t}^{\alpha_l^1}}. \tag{6}$$

Consider any two set of solutions $(u_t^0, \alpha_l^{0,1})_{l\in L, t\in T}$ and $(u_t^1, \alpha_l^{1,1})_{l\in L, t\in T}$ to the inequalities in Proposition 1 given $(\lambda_t)_{t\in T}$ and δ. Thus, we have

$$u_s^0 - u_t^0 \leq \lambda_t \delta^{-t} \left[\boldsymbol{p}_t'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \left(\boldsymbol{\alpha}^{0,1} \odot \frac{\boldsymbol{p}_t}{\boldsymbol{a_t}} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a}_s - \boldsymbol{a}_t) \right]$$
$$u_s^1 - u_t^1 \leq \lambda_t \delta^{-t} \left[\boldsymbol{p}_t'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \left(\boldsymbol{\alpha}^{1,1} \odot \frac{\boldsymbol{p}_t}{\boldsymbol{a_t}} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a}_s - \boldsymbol{a}_t) \right],$$

where $e^{-(\omega_{l,t} - \alpha_l^0)}$ has been substituted by its expression from equation (6). Multiplying the first inequality by $\theta \in [0, 1]$, the second by $1 - \theta$, and summing them up yields

$$u_s^\theta - u_t^\theta \leq \lambda_t \delta^{-t} \left[\boldsymbol{p}_t'(\boldsymbol{c}_s - \boldsymbol{c}_t) + \left(\boldsymbol{\alpha}^{\theta,1} \odot \frac{\boldsymbol{p}_t}{\boldsymbol{a_t}} \odot \boldsymbol{c}_t \right)' (\boldsymbol{a}_s - \boldsymbol{a}_t) \right],$$

where $u_t^\theta = \theta u_t^0 + (1-\theta)u_t^1$ for all $t \in T$ and $\boldsymbol{\alpha}^{\theta,1} = \theta\boldsymbol{\alpha}^{0,1} + (1-\theta)\boldsymbol{\alpha}^{1,1}$. This shows that the set of elasticities of price with respect to shopping intensity is convex conditional on $(\lambda_t)_{t\in T}$ and δ.

Proof of Proposition 3

Assumption 1 states that the price function for any good $l \in L$ is given by:

$$\log(p_{l,t}) = \alpha_l^0 + \alpha_l^1 \log(a_{l,t}) - \omega_{l,t}.$$

Summing this equation across goods and dividing by L yields

$$\overline{\log(p_{l,t})} = \frac{1}{L}\sum_{l=1}^{L}\left[\alpha_l^0 + \alpha_l^1 \log(a_{l,t})\right] - \bar{\omega}_{l,t},$$

where $\overline{\log(p_{l,t})}$ denotes the average log price paid and $\bar{\omega}_{l,t}$ denotes the average search ability. Further taking the expectation simplifies the equation to

$$\mathbb{E}\left[\overline{\log(p_{l,t})}\right] = \frac{1}{L}\sum_{l=1}^{L}\left(\mathbb{E}\left[\alpha_l^0\right] + \mathbb{E}\left[\alpha_l^1\right]\log(a_{l,t})\right),$$

where Assumption 4 was used to eliminate the expected average search ability. By Assumption 2, the above can be written as

$$\mathbb{E}\left[\overline{\log\left(p_{l,t}^*\right)}\right] = \frac{1}{L}\sum_{l=1}^{L}\left(\mathbb{E}\left[\alpha_l^0\right] + \mathbb{E}\left[\alpha_l^1\right]\log(a_{l,t})\right).$$

Taking the derivative with respect to $\log(a_{l,t})$ and invoking Leibniz integration rule, one gets

$$\mathbb{E}\left[\frac{\partial\overline{\log\left(p_{l,t}^*\right)}}{\partial\log(a_{l,t})}\right] = \frac{1}{L}\mathbb{E}\left[\alpha_l^1\right].$$

Finally, summing this equation for each $l \in L$ and dividing by L gives

$$\frac{1}{L}\sum_{l=1}^{L}\mathbb{E}\left[\frac{\partial\overline{\log\left(p_{l,t}^*\right)}}{\partial\log(a_{l,t})}\right] = \frac{1}{L}\mathbb{E}\left[\overline{\alpha^1}\right],$$

where $\overline{\alpha^1} := \frac{1}{L}\sum_{l=1}^{L}\alpha_l^1$ is the average shopping technology across goods.

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