A General Revealed Preference Test for Quasi-Linear Preferences: Theory and Experiments

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Abstract

We provide a generalized revealed preference test for quasi-linear preferences. The test applies to nonlinear budget sets and nonconvex preferences and can be used in contexts such as taxation and nonlinear pricing. We use this test to evaluate the prevalence of quasi-linear preferences in a laboratory experiment on consumption. We find that half of the subjects who satisfy the Generalized Axiom of Revealed Preferences also satisfy the criteria for quasi-linear preferences.

Keywords: revealed preferences; quasi-linear preferences; lab experiments

JEL codes: D12; D11; C91

1 Introduction

It is difficult to overstate the importance of the assumption of quasi-linear (QL) preferences in both theoretical and empirical economics. The assumption plays a crucial role in mechanism design, the theory of the household, and applied welfare analysis. It is, for instance, a necessary assumption for the Revenue Equivalence theorem (Myerson, 1981; Krishna, 2009), the existence

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of the truth-revealing dominant strategy mechanism for public goods (Green and Laffont, 1977), and the Rotten Kids theorem (Becker, 1974; Bergstrom and Cornes, 1983). It is also a frequently invoked assumption in applied welfare analysis (Domencich and McFadden, 1975; Allcott and Taubinsky, 2015). The first contribution of our paper is to provide a new test for QL preferences that has many empirical applications. The second contribution is to provide the first empirical test of QL preferences in a laboratory setting.

Contribution We provide criteria for a set of observed choices on nonlinear budget sets being generated by quasi-linear preferences that are not necessarily convex. Our criteria are based on the observation that when preferences are QL, they must also satisfy the property of *cyclical monotonicity* (see, e.g., Rochet, 1987). Our contribution lies in demonstrating that cyclical monotonicity holds for a larger class of choice environments than previously established. We show that Forges and Minelli (2009)'s generalization of revealed preferences tests to nonlinear sets extends to tests of QL. This allows testing for QL preferences in some strategic environments. When the choice sets are linear, however, the condition we identify is equivalent to the definition of *cyclical monotonicity* in Brown and Calsamiglia (2007). These conditions are necessary and sufficient for choices to be rationalized by a QL utility function. We provide examples that show why it is important to consider nonlinear budget sets.

We also provide an empirical test for QL preferences in a laboratory experiment. As we discuss in the paper, the laboratory setting has advantages over consumer data in testing for QL. In our experiment, we mimic different consumption groups by offering gift cards at discounted prices. We implement a five-good and a three-good treatment over 30 different budgets to test whether subjects' preferences can be rationalized by QL preferences, and we find support for the Generalized Axiom of Revealed Preferences (GARP). For 29 out of 64 subjects in the five-good treatment and 41 out of 63 subjects in the three-good treatment, Afriat's critical cost efficiency index (CCEI) is above 0.90. This compares well to the results of Mattei (2000), who provides one of the few experimental tests of rational behavior over many consumption goods.[1] Regarding QL, we find that the preferences

[1]If we consider a CCEI level of .95, the predictive success indices (Selten, 1991) for Mattei (2000)'s Experiment I

of 15 out of 64 subjects in the five-good treatment and 20 out of 63 subjects in the three-good treatment satisfy QL with Afriat's CCEI above 0.90. This amounts to about half of the subjects' preferences satisfying GARP. Remarkably, this proportion is similar for the five-good treatment and the three-good treatment, which indicates that the measured proportion of QL subjects is robust to the complexity of the choice environment.

Related Literature Revealed preference theory is attractive because of its robustness to functional form assumptions regarding preferences. Beginning with the work of Richter (1966) and Afriat (1967), revealed preference theory has been used to test both individual and collective decision-making (see Chambers and Echenique, 2016, for a comprehensive overview of the results). It has also been use to test theories of consumer behavior in the lab. Applications include tests for social (e.g., Andreoni and Miller, 2002; Fisman et al., 2007; Porter and Adams, 2015), risk (e.g., Choi et al., 2007), and time preferences (e.g., Andreoni and Sprenger, 2012).

Relevant to our pursuit, some of these experiments have been conducted using real consumption goods. Cox (1997) uses the data collected by Battalio et al. (1973) to test the consistency of patients' behavior at a mental hospital. Mattei (2000) tests the consistency of college students' choices of snacks and stationery. Brocas et al. (2018) tests the consistency of older adults' and college students' choices of food items. In our study, we use gift cards that allow us to provide a set of goods that mimics the goods our subjects would choose to buy outside of the lab. Closer to our setting, Costa-Gomes et al. (2016) use real consumption goods (headphones). However, to provide added realism in our setting, we use choice bundles consisting of multiple goods rather than choices between different types of similar consumption goods.

Recently, there has been interest in revealed preference tests for QL preferences in the context of linear budgets. Brown and Calsamiglia (2007) propose a revealed preference test for the case of concave preferences, while Nocke and Schutz (2017) discuss the corresponding integrability problem without assuming concavity. Cherchye et al. (2015) extends Brown and Calsamiglia

and Experiment II are .57 and .53, respectively. The predictive success index for our experiment is .57.

(2007)'s test to generalized QL while maintaining the concavity of the utility and the linearity of budgets. Allen and Rehbeck (2018) provide a measure for QL misspecification and use scanner data to evaluate how this misspecification varies with the level of aggregation of the data.[2] They find that while QL fails at the individual level, it represents the data well from the perspective of a representative agent. Chambers and Echenique (2017) show that QL utility in the setting of combinatorial demand is equivalent to the law of demand, a condition that is simpler than cyclical monotonicity. As we will discuss, our approach provides the least restrictive test for QL preferences, and our experiment provides direct evidence that QL is empirically relevant at the *individual* level. This is important since testing for quasi-linear preferences with field data might require making ancillary assumptions due to aggregation. For instance, empirical analysis using scanner data usually ignore bundling and use of coupons. The potential biases emerging from this practice can be avoided in experimental settings. Our experiments therefore complement these approaches nicely.

Structure The remainder of this paper is organized as follows. Section 2 presents our theoretical framework, Section 3 presents our experimental design and the empirical results, and Section 4 concludes the paper.

2 Theoretical Framework

In this section, we discuss the necessary and sufficient conditions for choices to be rationalized by a QL utility function.

Consider a space of alternatives $Y = X \times \mathbb{R}$, where $X \subseteq \mathbb{R}^n_+$.[3] We denote an element of this set as $(x, m) \in Y$, where $x \in X$ and $m \in \mathbb{R}$. Intuitively, x is a bundle of consumption goods and m is

[2] We test for quasi-linearity in a Spanish consumer data panel (Crawford, 2010) and, like Allen and Rehbeck (2018), we find little evidence of QL at the individual level. We briefly comment on these results in the Experimental Results section and present the results in an appendix.

[3] Formally, we do not need to assume that X is an arbitrary set endowed with an order $\geq$. The same result can be obtained for a non-ordered space. This is the case when X is used to represent a combinatorial demand problem.

an amount of money. A QL utility function takes the following form:

$$v(x, m) = u(x) + m,$$

where $u : X \to \mathbb{R}$ is a real valued sub-utility function.

Let $E = ((x^t, m^t), B^t)_{t=1}^T$ be a consumption experiment, where (x^t, m^t) is the bundle chosen from budget $B^t \subseteq Y$ and T is the total number of decisions made. Let C be the set of all chosen bundles of goods (i.e., all x^t) in experiment E. We assume that budgets are downward closed[4] and have compact borders and that there is a strictly decreasing function $m^t(x)$ such that $m^t(x^t) = m^t$.

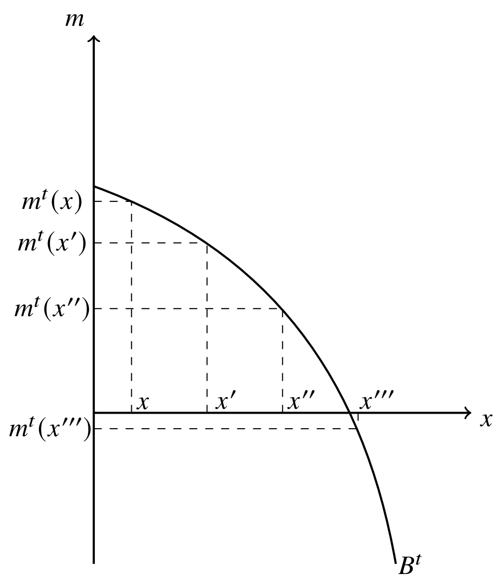


Figure 1: Obtaining $m^t(x)$.

Figure 1 illustrates how one can construct $m^t(x)$, the maximum value of m such that $(x, m^t(x)) \in B^t$. Note that $m^t(x)$ can be negative; indeed, for a high enough value of x, it *will* be negative. In Forges and Minelli (2009)'s framework, a gauge function $g^t(x, m)$ of the budget set (x, m) is a function such that $x \in B^t$ if and only if $g^t(x, m) \leq 0$. We can then define $m^t(x)$ as follows:

$$m^t(x) = \underset{m \in \mathbb{R}}{\text{argmax}}\{m : g^t(x, m) \leq 0\}.$$

[4]That is, if $x \in B^t$, then $y \in B^t$ for every $y \leq B^t$.

For the case of linear budgets, $m^t(x) = \frac{I - p_x x}{p_m}$, where I stands for income, p_x the price of the good(s) x, and p_m the price of money. We assume that $m^t = m^t(x^t)$ in order to avoid a violation of monotonicity in m. Since the budget is downward closed for every $x \in X$, $(x, m^t(x)) \in B^t$, we allow $m^t(x)$ to be negative, as this technical assumption simplifies the analysis. If we consider m to be money, then a negative consumption of money can be interpreted as borrowing, and budgets being downward closed can be interpreted as the absence of a binding liquidity constraint.[5]

Definition 1. *A consumption experiment E can be* ***rationalized by a QL utility*** *(QLU)* ***function*** *if there is a function $v(x, m) = u(x) + m$ such that*

$$u(x^t) + m^t \geq u(x) + m \text{ for every } (x, m) \in B^t.$$

Definition 2. *A consumption experiment E satisfies* ***cyclical monotonicity*** *if for every $x^{k_1}, \ldots, x^{k_n} \in C$,*

$$\sum_{k=1}^{n} m^{k_j}(x^{k_j}) - m^{k_{j+1}}(x^{k_j}) \geq 0,$$

where $k_{n+1} = k_1$.

Cyclical monotonicity was introduced by Rockafellar (1970), and its importance in characterizing QL was established by Rochet (1987) and Brown and Calsamiglia (2007). The version of cyclical monotonicity we use is equivalent to the standard definition up to a reordering of the terms.

Figure 2 shows an example of a violation of QL. To see this, suppose that the agent makes decisions according to a QLU function. Since y^s is chosen from B^s, it must be the case that the agent prefers y^s to $(x^t, m^s(x^t))$, and thus $(x^s, m^s(x^s) + [m^t(x^t) - m^s(x^t)])$ will be preferred to y^t (from QL). However, since $(x^s, m^s(x^s) + [m^t(x^t) - m^s(x^t)])$ is in the interior of B^t, y^t is revealed to be preferred instead, which is a contradiction.

We now establish the main result for this section, whose proof is provided in Appendix A.

Theorem 1. *The following statements are equivalent:*

[5] This assumption is technical and not crucial for our result. Imposing a liquidity constraint would require adding notation complicating the exposition without providing new insights.

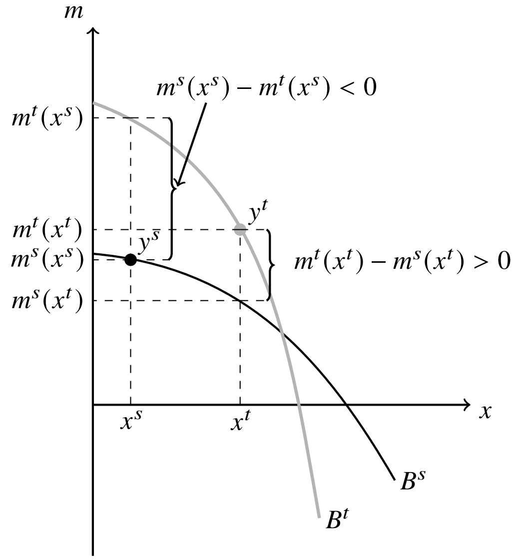


Figure 2: Data that are inconsistent with QLU rationalization.

(1) Consumption experiment E can be rationalized by a QLU function.

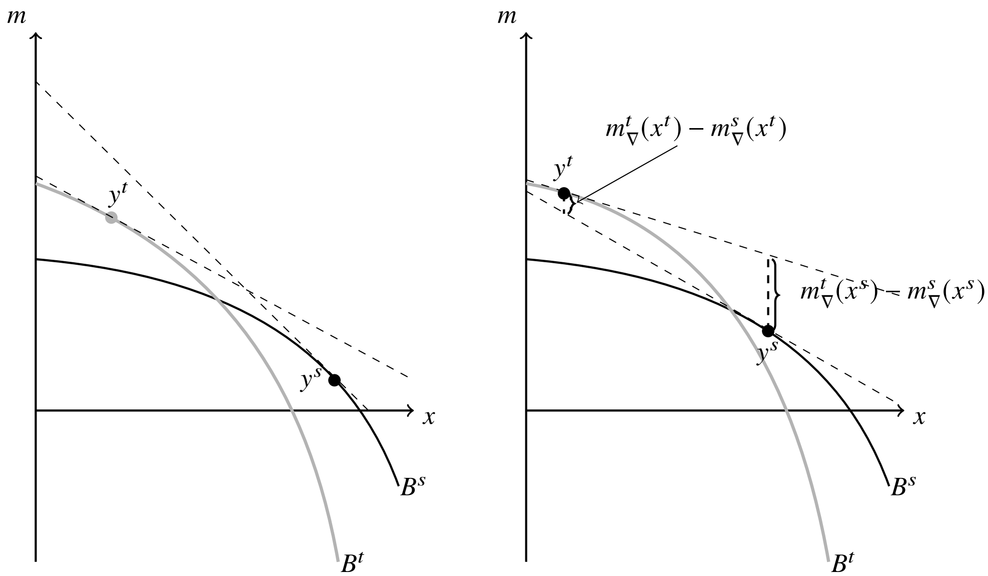
(2) Consumption experiment E satisfies cyclical monotonicity.

(3) There is a monotone function $u : C \to \mathbb{R}$ such that

$$u(x^t) - u(x^s) \geq m^t(x^s) - m^t(x^t) \text{ for every } t, s \in \{1, \ldots, T\}.$$

Before proceeding, we make two remarks that illustrate the usefulness of our result. First, we will illustrate how restrictive the assumption of the concavity of the utility function is. Second, we will show that without additional assumptions regarding the structure of budgets, the requirement of cyclical monotonicity cannot be further simplified.

Figure 3 illustrates how restrictive the assumption of concavity of the utility function is when budgets are nonlinear. Figure 3(a) shows that a consumption experiment can satisfy cyclical monotonicity, i.e., be QL rationalizable, but fail GARP for the linearized version of the budgets (see Matzkin, 1991). The dashed lines show the linearized budgets as presented in Forges and Minelli (2009), assuming that prices are constant and equal to the gradient of the gauge function of the budget set at the chosen point. Figure 3(b) shows that a consumption experiment can satisfy cyclical



(a) Nonconcave utility (b) Nonconcave QL utility

Figure 3: How restrictive the concavity of the utility function is.

monotonicity, i.e., be QL rationalizable, but fail to have a *concave* QL rationalization. Cyclical monotonicity fails in the linearized budgets in the example since $m^t_\nabla(x^s) - m^s_\nabla(x^s) > m^t_\nabla(x^t) - m^s_\nabla(x^t)$, where m^t_∇ is the amount of m computed using the gradient of the border of the budget as the fixed price.

Finally, Figure 4 shows that transitivity plays a nontrivial role in testing QL when budgets are nonlinear. It is known that if Y is two-dimensional and the budgets are linear, then transitivity does not have testable implications (i.e., the weak axiom of revealed preferences [WARP] is equivalent to the strong axiom of revealed preferences [SARP]) (Rose, 1958). This result has been extended to the case of homothetic preferences by Heufer (2013) and to the case of QL by Chambers and Echenique (2017), who show that in the context of combinatorial demand, the law of demand is equivalent to cyclical monotonicity if the budgets are linear. The example in Figure 4 shows that, even in a two-good setting, transitivity is crucial for testing QL if the budgets are nonlinear. In the example, there are no pairwise violations of cyclical monotonicity since (1) $y^s = (x^s, m^s(x^s))$ lies on the intersection of B^r and B^s, while $y^r = (x^r, m^r(x^r))$ is not achievable with budget B^s; (2) $|m^t(x^t) - m^s(x^t)| = |m^s(x^s) - m^t(x^s)|$, since those segments of the budgets are parallel; and (3)

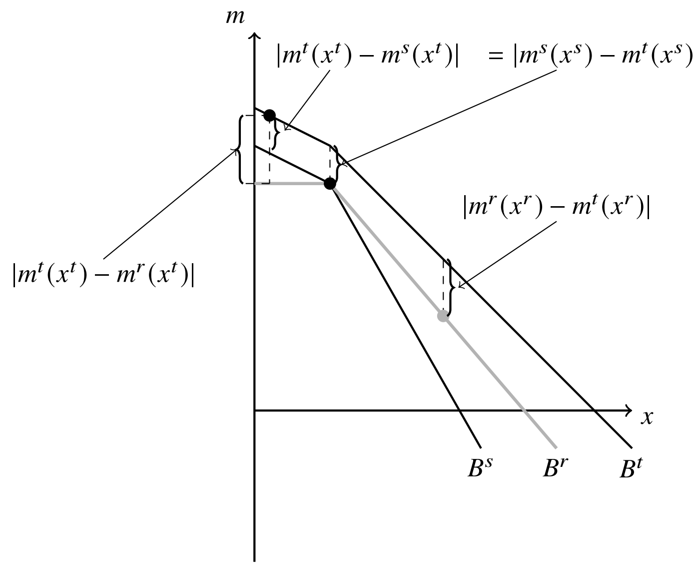


Figure 4: Violation of cyclical monotonicity in a 2-dimensional budget.

$|m^t(x^t) - m^r(x^t)| > |m^r(x^r) - m^t(x^r)|$. However, if we consider the sequence r, t, s there is a violation of cyclical monotonicity since $m^r(x^r) - m^t(x^r) < 0$ and $|m^r(x^r) - m^t(x^r)| > |m^t(x^t) - m^s(x^t)|$, while $m^s(x^s) - m^r(x^s) = 0$.

In sum, our test significantly generalizes previous results.

3 Testing QL

In this section we present our experimental design and the results of the test of QL.

3.1 Experimental Design and Procedures

To test QL, we designed an experiment in which subjects were asked to make consumption decisions that resembled day-to-day allocations of their budget. Specifically, we asked subjects to allocate 100 tokens among a fixed set of goods, including cash. We varied the cost (in tokens) of each good across the consumption categories. For instance, a subject might be able to exchange a token for 25 cents' worth of a good in one menu and for 10 cents' worth of the same good in another menu. Since these decisions can be complex, we implemented two treatments: a five-good treatment and a three-good treatment. In the five-good treatment, subjects had to allocate the 100 tokens across five goods (including cash), and in the three-good treatment, subjects had to allocate the tokens across three goods (including cash).[6] The goods used in the five-good experiment were cash, a Fandango Gift Card, a Barnes & Noble gift card, a Gap gift card, and Mason Money (described below). In the three-good treatment we included only cash, a Barnes & Noble gift card, and Mason Money.

To be more specific, the unit of measurement for each commodity was \$1 and subjects were asked to allocate 100 tokens between the goods mentioned above, whose prices were denominated as tokens per dollar value of the commodity. Each subject made choices for 30 menus, one of which was chosen at random at the end of the experiment to be implemented (i.e. subjects received the bundle they chose for this budget). To maximize the power of the test (see Choi et al. (2007)), the prices were also chosen at random for each subject. The experiment was conducted with 127 George Mason University undergraduates (64 subjects in the five-good treatment and 63 subjects in the three-good treatment).[7]

To bring the field to the lab, we chose goods that were needed by and familiar to the subjects. Fandango is a movie-theater ticket distributor and represents spending on entertainment. Barnes & Noble is a book distributor and represents spending on necessities, since textbooks are a required expenditure for students. The Gap is a clothing store and represents spending on durable goods. Mason Money is George Mason University's internal monetary system, which can be used at any on-campus restaurant, and therefore represents food spending.

We chose these goods after consulting with students about their purchase habits. The commodities were chosen to minimize consumption transaction costs, as high transaction costs might prompt subjects to trade the gift cards and therefore favor the hypothesis of rationality or QL in preferences—for instance, subjects facing high transaction costs might always choose the cards with the best trade-in value. However, money cannot be withdrawn from Mason Money cards (see Terms and Conditions), and it is not transferable since it is linked to the students' photo IDs, and, to the extent possible, we used gift cards bearing the subject's name to reduce the transfer of cards

[6]We would like to thank Catherine Eckel for the suggestion to run the treatment with reduced amounts of goods.

[7]A complete explanation of the experimental design and procedures is provided in Appendix C.

across individuals. We only have data on the usage of the Barnes & Noble cards. We found that most subjects used these cards within a month after the experiment.

Figure 5 shows the experimental interface, programmed using oTree (Chen et al., 2016). The interface allowed several allocations to be tried before progressing to the next menu and enforced the restriction that allocation cound never exceed 100 tokens. As mentioned earlier, the set of prices was randomly selected for each menu.

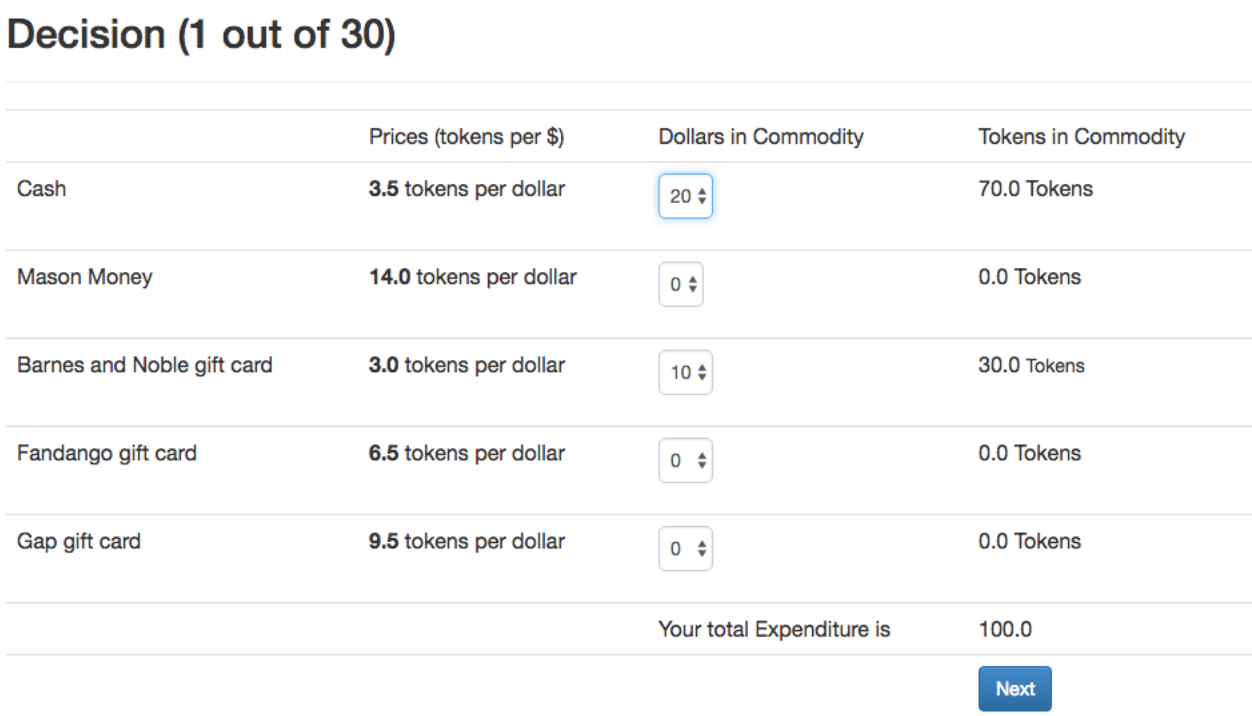


Figure 5: Experimental interface.

Table 1 presents descriptive statistics for the experimental data by treatment. The top panel shows the percentages of money allocated across the goods (dollars×tokens per dollar divided by the total expenditure of tokens). We observe that cash was the highest-demand good and the Gap card was the lowest-demand good. These proportions are comparable across treatments conditional on the categories common to both treatments. The second panel of Table 1 shows the price ranges from which prices were chosen. The price ranges were the same for both treatments and ensured a high variation in prices across the 30 menus. We should remark that in our experiments, subjects could acquire a significant amount of money in each category. Specifically, the maximum amount

Relative expenditures on the goods		
	3 Goods	5 Goods
Cash	58.66%	47.10%
Mason Money	25.36%	15.80%
Barnes & Noble	15.98%	14.14%
Fandango	–	12.22%
Gap	–	10.73%
Price ranges (tokens per $ value)		
	min	max
Cash	2.5	15
Mason Money	2.5	15
Barnes & Noble	2.5	9.5
Fandango	2.5	6.5
Gap	3	10
Patterns of choice by menu		
	3 Goods	5 Goods
Chose cheapest	42.70%	19.48%
Cash only	48.10%	36.20%
One good	73.33%	58.85%
Two goods	23.39%	36.61%
Three goods	3.28%	4.48%

Table 1: Descriptive statistics.

of money in cash was $40, for Fandango it was $35, for Barnes & Noble it was $40, for Mason Money it was $40, and for the Gap it was $33. The average earning in the experiment was $19.06 (dollar equivalent).

The bottom panel of Table 1 shows the subjects' patterns of behavior across menus. First, we report the proportion of menus that had all of the tokens allocated to the cheapest good: 19.48% in the five-good treatment and 42.70% in the three-good treatment. Second, we report the proportion of menus that had all of the tokens allocated to cash: 36.20% in the five-good treatment and 48.10% in the three-good treatment. Next, we report the proportion of subjects that had all of the tokens allocated to one good only: 58.85% in the five-good treatment and 73.33% in the three-good treatment. Finally, we report the proportion of menus that exhibited choices across more than one good. In most of the cases, tokens were allocated to one or two goods. This is partially a consequence of the fact that some accounts had a minimum balance requirement.[8] However, we should mention that our test of QL applies to cases with nonlinear budget sets such as these and has no restrictions regarding corner choices.

3.2 Assessing the severity of violations of rationality

To assess the prevalence of QL preferences, we need to adopt a behavioral benchmark for comparison. A natural benchmark is the existence of locally nonsatiated utility (LNU) that rationalizes the data. For the choice experiment, this is equivalent to satisfying GARP, which has been tested in several domains using experimental methods (Mattei, 2000; Harbaugh et al., 2001; Andreoni and Miller, 2002; Choi et al., 2007, 2014).

Because the test for QL is binary – either the test is passed or it is not – we need to consider the possibility that people might make mistakes. To account for this possibility, we use Afriat (1973)'s CCEI as a measure of distance to rationality. For any $e \in (0, 1]$, define $B^t(e) = \{y \in Y : \frac{y}{e} \in B^t\}$. The CCEI for GARP (QL) is the maximum $e \in (0, 1]$ such that a consumption experiment $(y^t, B^t(e))$ is consistent with GARP (QL). Consider a basic case of linear budgets, as in Afriat (1973). We are searching for the maximum $e \in (0, 1]$ such that given e, the (strict) revealed preference relation R (P) defined via $y^t R y$ ($y^t P y$) holds if and only if $p^t y (<) \leq eI^t$, where p^t denotes prices and I^t denotes income. We use an equivalent definition that works in the context of nonlinear budget sets as well: we divide both sides of the inequality by e to obtain the equivalent definition for e's (strict) revealed preference relation $p^t \frac{y}{e} (<) \leq I^t$.

An additional way to assess the strength of our design is to compare the pass rates of the actual subjects and the pass rate of a subject choosing at random. This measure, referred as the **predictive success index** (PSI), was originally proposed by Selten (1991). The PSI is defined as the difference between the share of people that satisfy an axiom at the given e and the probability that uniform random choices will satisfy the axiom at the same e. This index ranges between -1 and 1, with -1 meaning that no subject passes the test when any person choosing at random would pass with

[8]The highest minimum amount was imposed by Fandango ($15).

probability one, and 1 meaning that every subject passes the test when no person choosing at random would have done so. To estimate the probability that uniform random choices will satisfy the axiom we use the Monte Carlo method with 1000 simulated random agents for each set of prices.[9]

3.3 Experimental Results

In this subsection, we present the main results of the experiments. Figure 6 shows the distribution of Afriat's CCEI index for GARP and QL in the five-good and three-good treatments. The mean CCEI for GARP in the five-good treatment was 0.81. If subjects were instead choosing at random, the CCEI for GARP would have been 0.75.[10] The mean CCEI for GARP in the three-good treatment was 0.88. This number would have been 0.56 if subjects were choosing at random.[11] The difference is significant ($p < .001$). Turning to QL, the mean CCEI for QL in the five-good treatment was 0.69 for actual subjects' choices and 0.49 for random choices.[12] This difference is significant ($p < .001$). The mean CCEI for QL in the three-good treatment was 0.76 for actual subjects' choices and 0.46 for random choices.[13] This difference is also significant ($p < .001$). Finally, we find no significant difference in the level of the CCEI between the five-good treatment and the three-good treatment.

Table 2 provides an alternative presentation of the results by giving the pass rates for GARP and QL with an Afriat's CCEI of 0.9 or higher. That is, we take any subjects with a CCEI of 0.9 or higher to have passed GARP (QL). The second column presents Bronars (1987)'s power for the test. The last column presents the PSI. Confidence intervals for the pass rates and Bronars' power are obtained using the Clopper-Pearson procedure. Confidence intervals for the PSI are obtained using the procedure in Demuynck (2014). Before we present the results of the test, we note that Bronars' power for both the GARP and the QL tests are high. Similarly, the confidence intervals

[9]We allow the choices of random subjects to be real numbers but require them to respect minimum consumption requirements.

[10]The distributions of the CCEI are also different based on the Kolmogorov-Smirnov test ($p < .001$).

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[12]The distributions are also different based on the Kolmogorov-Smirnov test ($p < .001$).

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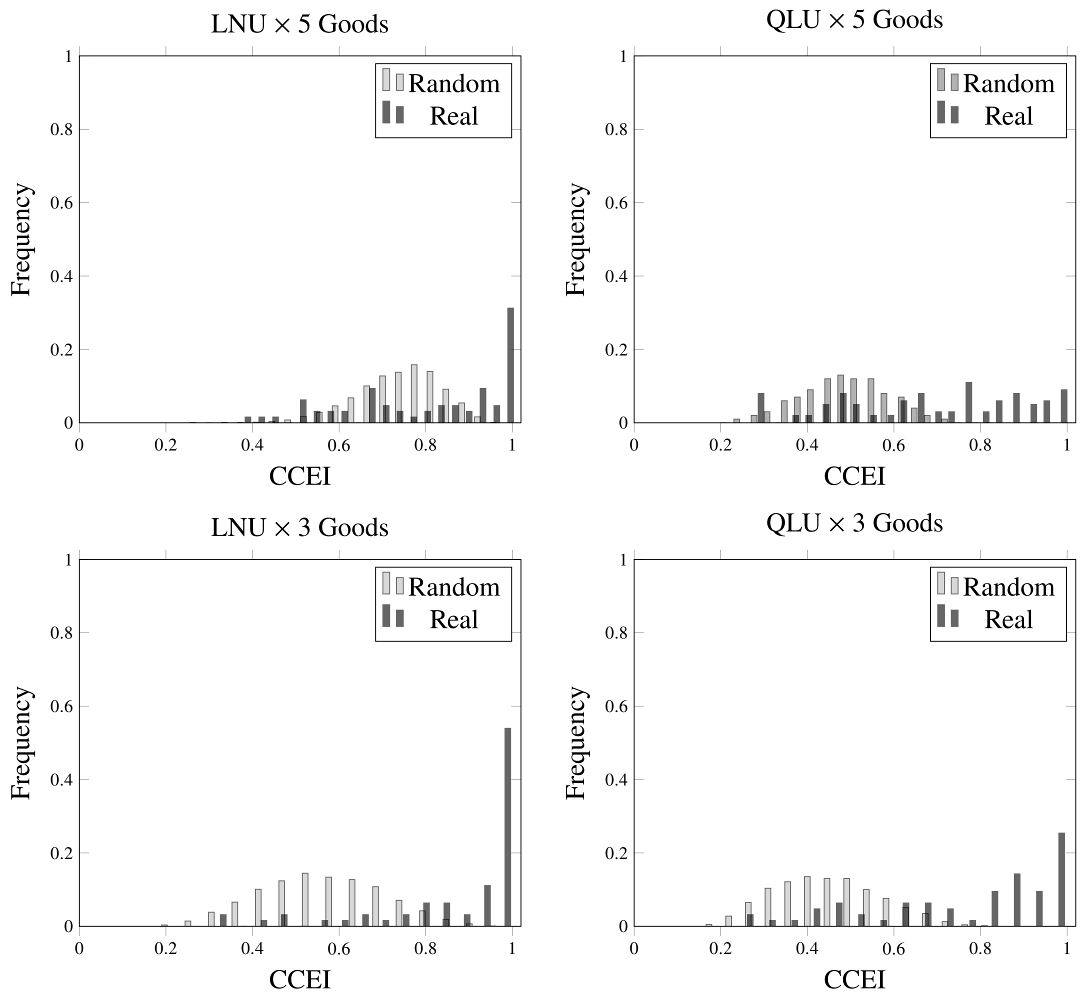

Figure 6: CCEI distribution for GARP and QL.

for the PSI for GARP and QL are well above 0. This gives us confidence in the robustness of our results.

Twenty-nine out of 64 subjects (45%) in the five-good treatment satisfy GARP with a CCEI of at least 0.9. In the three-good treatment, 41 out of 63 subjects (65%) satisfy GARP with a CCEI of at least 0.9. Fifteen out of 64 subjects (23%) in the five-good treatment pass the QL test with a CCEI of at least 0.9. Twenty out of 63 subjects (32%) in the three-good treatment pass the QL test with a CCEI greater of at least 0.9. This suggests that QL is more prevalent in the three-good treatment. Note, however, that the QL pass rates conditional on GARP are very close across the treatments. About half of the subjects satisfying GARP also satisfy QL. These patterns are robust

Theory	Pass Rate	Bronars' Power for the Test	PSI
Three-Good Treatment			
GARP (unconditional)	41 (65.08%)	99.54%	0.65
95% conf. interval	(52.03%–76.66%)	(99.34%–99.69%)	(0.53–0.76)
QL (conditional on GARP)	20 (48.78%)	99.22%	0.45
95% conf. interval	(32.88%–64.87%)	(98.97%–99.42%)	(0.30–0.60)
Five-Good Treatment			
GARP (unconditional)	29 (45.31%)	96.64%	0.42
95% conf. interval	(32.82%–58.25%)	(96.22%–97.11%)	(0.30–0.54)
QL (conditional on GARP)	15 (51.72%)	99.70%	0.51
95% conf. interval	(32.53%–70.55%)	(99.54%–99.82%)	(0.33–0.70)

Table 2: Results for experimental data (CCEI=.9).

to different CCEI cut-off criteria (see Appendix B.1).

Complexity appears to affect the observed level of rationality (and QL). Behavior in the five-good treatment is noisier than in the three-good treatment. This can be explained by limited attention, with subjects paying attention to only a subset of the goods. However, this would require attention to change in ways that are contradictory to rational decision-making (e.g., not always paying attention to the cheapest options).[14] We note that it is harder to pass GARP by choosing at random in the three-good treatment than in the five-good treatment. The larger the dimension of the problem, the easier it is to pass GARP. That is, in the stricter test for GARP (QL), we find behavior that is more consistent with theory. The PSI for QL is similar across treatments.

Figure 7 presents examples of the demand functions for different types of subjects for both the three-good and the five-good treatments. The first two graphs show the demand function for cash for two subjects whose preferences are not consistent with GARP (CCEI $\leq$ .85).[15] The second two graphs show the demand function for cash for two subjects whose preferences are consistent with GARP but not with QL (CCEI for GARP $\geq$ .95 and for QL $\leq$ .8). The last two graphs show the demand function for cash for two subjects whose preferences are consistent with QL (CCEI

[14] Demuynck and Seel (2018) provide a framework for conducting revealed preference analysis in the presence of limited attention. Our test can be similarly adapted for this purpose.

[15] Since GARP is equivalent to the existence of locally nonsatiated utility fuction (LNU), we use these terms interchangeably.

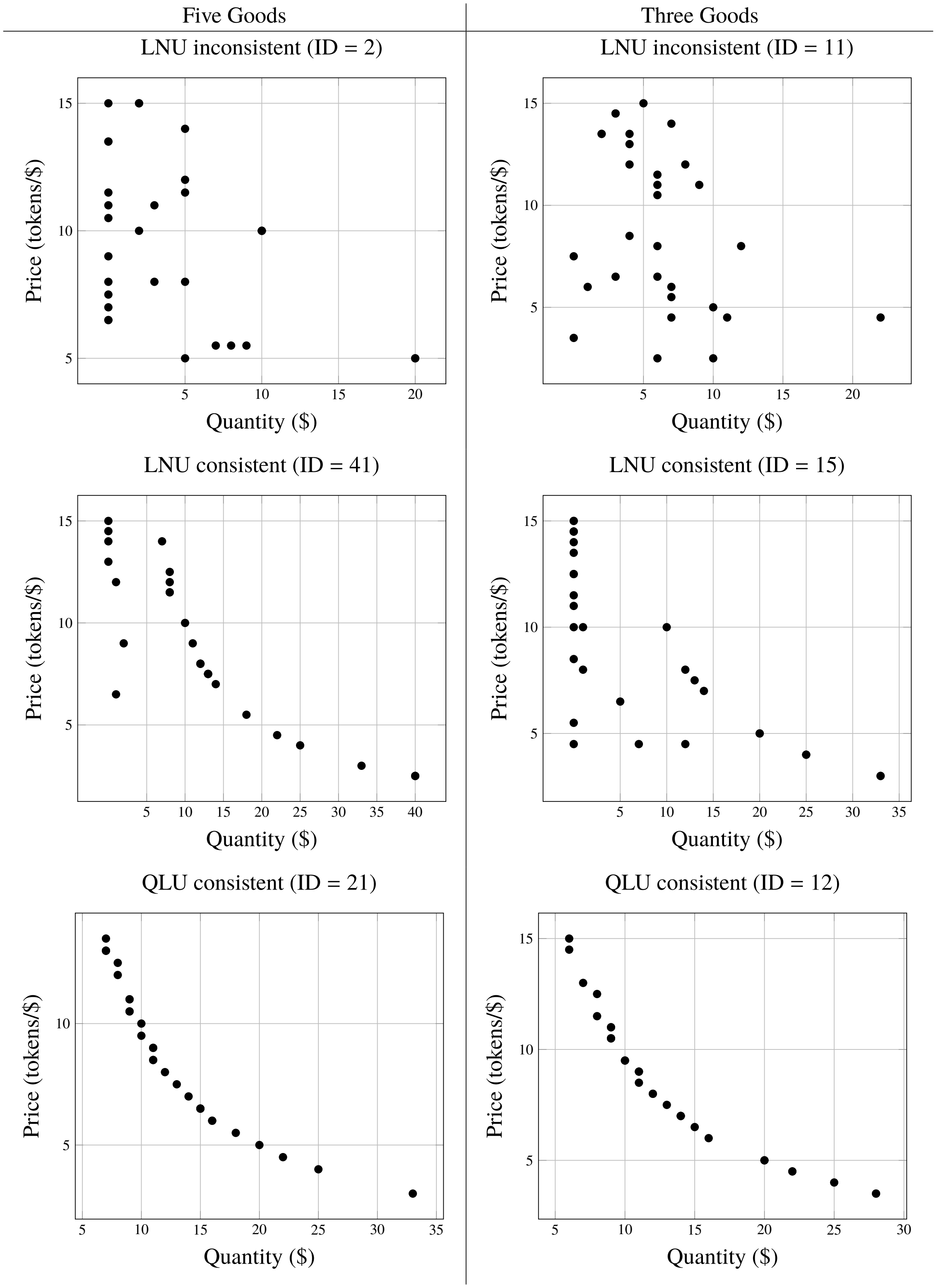

Figure 7: Examples of demand functions for cash.

for QL $\geq .95$). Among the subjects whose preferences are not consistent with GARP, we can see that there is no clear demand function for cash. For those whose preferences are consistent with GARP but not with QL, we can see that there are several possible demand functions, presumably with different slopes. Finally, for the subjects whose preferences are consistent with QL, we see a unique demand function for cash. We should note that it is not the case that subjects whose preferences are consistent with QL do not consume any goods except cash; rather, we observe that those subjects spend a larger proportion of their budget on cash than on any other commodity. In sum, we find a robust empirical regularity in that both GARP and QL are well represented in the subjects' behavior. Half of the subjects whose preferences satisfy GARP also satisfy QL.

While our experiments provide evidence in favor of the assumption of QL preferences in a *field in the lab* setting, an analysis of scanner data suggests the opposite (see Allen and Rehbeck, 2018).[16] Moreover, application of our test to the Spanish Continuous Family Expenditure Survey (see Appendix B) shows that only around 1 percent of households exactly satisfy QL. Analysis of QL preferences using observational data is complicated by issues of measurement and aggregation, which are absent in a controlled lab setting such as ours. In other words, a test of QL preferences using observational data is a joint test of preferences and measurement assumptions. A second reason why there might be a difference between tests using observational data and laboratory experiments is that QL holds only locally, i.e., when the stakes are small. While stakes are larger in the Spanish data, the stakes in the scanner data are arguably comparable to the stakes our laboratory subjects faced once we adjust for differences in income and household size between

[16]One of the reasons why Allen and Rehbeck (2018) found inconsistency with QL preferences at the individual level can be the fact that individual discounts agents face at each purchase are not accounted for and prices are just treated as linear. Echenique et al. (2011) who constructed the data set used by Allen and Rehbeck (2018) directly claim that the prices used is the shelf price and therefore does not take into account household's use of coupons and/or discounts. At the same time 86% of the transactions are conducted at the shelf prices. Hence, the amplitude of error at the individual level can be too large to be reasonably accounted as measurement error, while looking at the aggregate level allows average out possible effects of nonlinearities in the prices. That is also consistent with the fact that Allen and Rehbeck (2018) find rather evidence for consistency with QL preferences at the aggregate level.

these two populations. This suggests that laboratory and field studies are complementary. While we cannot speak to the effect of larger stakes in our experiment, we can say something about the complexity of the environment. The absolute (unconditional) level of consistency with QL (and GARP) decreases with the number of goods in a budget. This alone can explain the difference in the level of consistency between QL preferences in the lab and in the field and suggests that more work is needed to understand the breakdown of rationality in complex environments (see Gabaix, 2014). We should remark that testing for QL using household consumption data or scanner data requires making assumptions about the actual shape of the budget sets faced by agents. As discussed in the theory section, if the assumption of the linearity of budget sets fails, the test might reject QL too often. The laboratory setting therefore allows us to provide a more direct test for QL preferences.

4 Conclusions

We provide necessary and sufficient condition for a set of observed choices to be rationalizable by a QL utility function. This condition applies to choices over compact and downward closed budget sets and does not require the utility function to be concave. We conduct the first laboratory experiment to test whether preferences are QL. We find that about half of the subjects whose preferences satisfy GARP are also consistent with QL preferences. This result is robust to the number of goods among which subjects have to choose.

An important advantage of the test of QL that we present here is that it applies to a large class of problems. First, it applies to consumer problems in the presence of distortions due to taxes, subsidies, or nonlinear pricing. Second, it can also be extended to a test for QL preferences in strategic situations where an assumption of QL preferences might be invoked (e.g., auction theory). Regarding our empirical evidence, we show that under tight experimental conditions, QL preferences are empirically relevant in individual decision-making.

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A Proof of Theorem 1

Proof. We prove the equivalence using the cyclical implication (1) ⇒ (2) ⇒ (3) ⇒ (1).

(1) ⇒ (2). Consider a function $v(y, p) = u(y) + m$ that rationalizes the consumption experiment. Then, for every sequence of chosen points $x^{k_1}, x^{k_2}, \dots, x^{k_n}$, the following is true:

$$u(x^{k_{j+1}}) + m^{k_{j+1}}(x^{k_{j+1}}) \geq u(x^{k_j}) + m^{k_{j+1}}(x^{k_j}),$$

where $k_{n+1} = k_1$. We can simplify this and obtain the following inequalities:

$$\begin{cases} m^{k_1}(x^{k_1}) - m^{k_1}(x^{k_2}) \geq u(y^{k_2}) - u(y^{k_1}), \\ m^{k_2}(x^{k_2}) - m^{k_2}(x^{k_3}) \geq u(y^{k_3}) - u(y^{k_2}), \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ m^{k_n}(x^{k_n}) - m^{k_n}(x^{k_1}) \geq (u(y^{k_1}) - u(y^{k_n}). \end{cases}$$

Summing up these inequalities, we obtain the following:

$$m^{k_1}(x^{k_1}) - m^{k_1}(x^{k_2}) + m^{k_2}(x^{k_2}) - m^{k_2}(x^{k_3}) + \ldots + m^{k_n}(x^{k_n}) - m^{k_n}(x^{k_1}) \geq 0.$$

This is exactly the cyclical monotonicity condition.

(2) ⇒ (3). Let

$$u(x^t) = \min\{m^{k_1}(x^{k_1}) - m^{k_1}(x^t) + \ldots + m^{k_n}(x^{k_n}) - m^{k_n}(x^{k_{n-1}})\}$$

over all sequences in the data, including those with repeating elements.[17] We will show that the minimum is well-defined. It will be enough to show that there will be no cycles in the minimal sequence, since the rest will follow from the fact that the minimum is taken over finite sums of finite numbers. So assume, to the contrary, that the minimum sequence contains a cycle; then we have

$$\ldots + \left(m^{k_n}(x^{k_n}) - m^{k_n}(x^{k_{n-1}}) + \ldots + m^{k_1}(x^{k_1}) - m^{k_1}(x^{k_n})\right) + \ldots.$$

However, cyclical monotonicity implies that this term is ≥ 0, and hence, excluding it would make

[17] In terms of graph theory, this is equivalent to searching for the shortest walk (on a weighted graph), rather than a shortest path (on a weighted graph). However, the shortest walk is not always well-defined. A sufficient condition for it to be well-defined is the absence of negative cycles, which is guaranteed by cyclical monotonicity if we define weights as $w_{s \to t} = m^t(x^t) - m^t(x^s)$.

the sequence even smaller. That contradicts the original assumption that the sequence was the smallest.

Further, we show that such a construction of u^t will guarantee that the system of inequalities is satisfied. For any $x^t, x^s \in C$ we want to show that

$$u(x^t) - u(x^s) \geq m^t(x^s) - m^t(x^t).$$

By the construction of $u(x)$, we can guarantee that

$$u(x^s) \leq m^t(x^t) - m^t(x^s) + u(x^t),$$

since

$$u(x^t) = m^{k_1}(x^{k_1}) - m^{k_1}(x^t) + \ldots + m^{k_n}(x^{k_n}) - m^{k_n}(x^{k_{n-1}})$$

for some (minimal) sequence, and we construct $u(x^s)$ using that minimal sequence. Recall that we allowed taking every sequence, including those with repeating elements, so we can add any element to the existing sequence and the utility level $u(x^s)$ will not exceed the value of the new extended sequence. Therefore,

$$u(x^t) - u(x^s) \geq u(x^t) - \left(m^t(x^t) - m^t(x^s) + u(x^t)\right) = m^t(x^s) - m^t(x^t).$$

(3) ⇒ (1). For every $x \in X$, let

$$u(x) = \min_{t \in \{1,\ldots,T\}} \{u^t + m^t(x^t) - m^t(x)\}.$$

Note that since m^t is continuous and monotone, so is $u(x)$.

First, we will show that for every $x^t \in C$, $u(x^t) = u^t$. Recall that the system of inequalities guarantees that for every s for which $m^s(x^t)$ is defined,

$$u^t \leq u^s + m^s(x^s) - m^s(x^t).$$

Therefore, $u(x^t) = u^t$. Next, we show that $v(x, m) \leq v(x^t, m^t(x^t))$ for every $(x, m) \in B^t$, where $v(x, m) = u(x)+m$. By the construction of $u(x)$, we know that $u(x) = \min_{t\in\{1,\ldots,T\}} \{u^t + m^t(x^t) - m^t(x)\} \leq u^t + m^t(x^t) - m^t(x)$. Therefore, $u(x) + m \leq u(x) + m^t(x) \leq u(x^t) + m^t(x^t)$. □

B (Online Only) Additional Empirical Results

This section consists of two parts. First, we present the robustness of the experimental results we obtained. Second, we present the results for observational data.

B.1 Robustness of the Lab Data

In this section, we present evidence for the robustness of the experimental results in Section 3. To do this, we present pass rates, Bronars' power for the test, and the PSI analysis—similar to Table 2—for alternative CCEI cut-off criteria.

The first panel of Table 3 presents results for a CCEI of 0.85, and the second panel presents results for a CCEI of 0.95. The results are similar to those for a CCEI of .9. We find that in all cases, both GARP and QL outperform random behavior. Moreover, we see that the conditional pass rates and conditional PSI for QL are significantly less than one, although they are not significantly different from those for GARP. Finally, we observe a reduction in the Bronars' powers for the pass rates and the PSIs as we move from the three-good to the five-good treatment. This observation is consistent with subjects becoming overwhelmed with choices and limited attention in the sense of Demuynck and Seel (2018). We find that the proportion of QL subjects conditional on passing GARP is never less than 28% and can be as high as 68%.

CCEI= .85			
Theory	**Pass Rate**	**Bronars' Power for Test**	**PSI**
Three-Goods Treatment			
GARP (unconditional)	44 (69.84%)	98.27%	0.68
95% conf. interval	(56.98%–80.77%)	(97.92%–98.58%)	(0.57–0.80)
QL (conditional on GARP)	30 (68.18%)	96.14%	0.65
95% conf. interval	(52.42%–81.39%)	(95.64%–96.60%)	(0.51–0.79)
Five-Goods Treatment			
GARP (unconditional)	31 (48.44%)	85.75%	0.34
95% conf. interval	(35.75%–61.27%)	(84.87%–86.60%)	(0.22–0.46)
QL (conditional on GARP)	19 (61.29%)	97.97%	0.60
95% conf. interval	(42.19%–78.15%)	(97.59%–98.30%)	(0.42–0.77)
CCEI= .95			
Theory	**Pass Rate**	**Bronars' Power for Test**	**PSI**
Three-Goods Treatment			
GARP (unconditional)	36 (57.14%)	99.98%	0.57
95% conf. interval	(44.05%–69.64%)	(99.91%–100.00%)	(0.45–0.69)
QL (conditional on GARP)	16 (44.44%)	99.89%	0.44
95% conf. interval	(27.94%–61.90%)	(99.77%–99.96%)	(0.28–0.61)
Five-Goods Treatment			
GARP (unconditional)	21 (32.81%)	99.86%	0.33
95% conf. interval	(21.59%–45.69%)	(99.73%–99.94%)	(0.21–0.44)
QL (conditional on GARP)	6 (28.57%)	100.00%	0.29
95% conf. interval	(11.28%–52.18%)	(99.94%–100.00%)	(0.09–0.48)

Table 3: Experimental results for CCEI= .85 and CCEI=.95.

B.2 Observational Data

For observational data, we use data from the Spanish Continuous Family Expenditure Survey (the Encuesta Continua de Presupuestos Familiares–ECPF) in this section. ECPF is a quarterly survey of households that are randomly rotated out at a rate of 12.5% per quarter. Participant households stay in the panel for up to eight consecutive periods. We use the panel from the years 1985 to 1997. For comparability with previous studies (Beatty and Crawford, 2011), we use the subsample that comprises only two-adult households with a single income earner in the nonagricultural sector. The data set consists of 21,866 observations and 3,134 households, which gives an average of seven consecutive periods per household. The expenditures of each household are aggregated into five groups: (1) Food, Alcohol and Tobacco, (2) Energy and Services at Home, (3) Non Durables, (4) Travel, and (5) Personal Services. For prices, we use the national quarterly consumer price index for the corresponding expenditure category.

Note that the longitudinal nature of the data requires assuming that preferences are stable over time. Also, we impute the same price index for all the households in a given quarter. The price variation across households is then obtained through their rotation in the sample. Also note that there is no record of money left over or of the total income of households. However, the test we construct is still applicable if we assume household income to be constant over different observational periods. This is likely an empirically valid assumption, given that households remain in the sample for two years.

The lack of knowledge of household income prevents us from learning how distant a household is from QL preferences. We can, however, test whether the behavior of a household is consistent with QL preferences at all. Formally, we test for the existence of an unobserved commodity (money) for which subjects' preferences are QL. We find that only 0.9% of the households pass the test. Moreover, the PSI given CCEI = 1 is almost zero ($\approx 5 \times 10^{-4}$) and is not significantly greater than zero.[18]

[18]The statistical interpretation of the PSI is taken from Demuynck (2014) .

C (Online Only) Instructions and Procedures

The experiment consisted of 30 independent decision problems. In each of these, subjects were asked to allocate tokens among five accounts (commodities): “Cash," “Mason Money," “Barnes & Noble gift card," “Fandango gift card," and “Gap gift card." There were additional restrictions due to the companies’ restrictions:

- The minimum positive balance for Mason Money was \$5.
- The minimum positive balance for the Barnes & Noble gift card was \$10.
- The minimum positive balance for the Gap gift card was \$10.
- For the Fandango gift card, the balance could be one of: \$0, \$15, \$25, \$35.

The resolution for each commodity (except the Fandango gift card) was \$1.

Before starting the experiment, instructions were read out aloud after each subject was given a paper copy of the instructions. All subjects took a quiz that tested their understanding of the decision-making task. At the end of the experiment, one of the decision problems was randomly chosen (from the discrete uniform distribution) and subjects were paid according to the decisions they made for that problem. We sent e-gift cards that could be used immediately to the subjects’ official GMU e-mail addresses. Cash choices were also paid at the end of the experiment, and Mason Money was sent to their Mason Money accounts.

The experiment was implemented using oTree (Chen et al. (2016)), and the demo version of the experiment is available at `https://qlt.herokuapp.com`. Next, we present the instructions for the five-goods treatment and, after that, the instructions for the three-goods treatment.

INSTRUCTIONS

Thank you for participating in today's experiment. Please remain silent during the experiment. If you have any questions, please raise your hand and the experimenter will assist you in private.

This is an experiment in individual decision-making. Your earnings from the experiment will depend in part on your decisions and on chance. Your earnings will **not** depend on the decisions of other participants. Please pay careful attention to the instructions as a considerable amount of money is at stake.

Your payment in today's experiment will not be lower than $15 equivalent. This will be paid to you at the end of the experiment in private.

You will face 30 decision problems. In each decision problem, you will be given 100 tokens to be divided among 5 commodities. The five commodities are:

- **Cash**

  You can choose any (integer) dollar amount of this commodity. The amount of your choice will be paid to you at the end of experiment.

- **Mason Money**

  This is a prepaid debit program that provides a fast, safe and convenient way to make purchases on and off campus. Mason Money is accepted at all cafes and restaurants on campus and is linked to your Mason ID.

- **Barnes and Noble gift card**

  Barnes and Noble is the largest retail bookseller in the United States, and a leading retailer of content, digital media and educational products in the country.

- **Fandango gift card**

  Fandango allows to buy tickets to more than 26,000 theaters nationwide. It is available online, and through their mobile and connected television apps.

- **Gap gift card**

  Gap is a US-based multinational clothing and accessories retailer. The card can be used in any store or the online store.

You will be asked to allocate your 100 tokens to each of these commodities for 30 different sets of prices for each commodity. Prices will range from 2.5 tokens per dollar to 15 tokens per dollar.

Prices are set up in the way that you can always buy an equivalent of $15. For instance, suppose that each commodity price is 5 tokens per dollar, then you can purchase $20 in cash, or $4 in each commodity.

Due to the restrictions set by companies on gift cards **additional restrictions** apply**:**

- If you purchase any positive amount of Mason Money, you should purchase at least $5.
- If you purchase any positive amount of Barnes and Noble gift card, you should purchase at least $10
- If you purchase any positive amount of Gap gift card, you should purchase at least $10.
- For Fandango gift card, you should purchase one of the following amounts: $0, $15, $25, $35.

Sample Screenshot:

Decision (1 out of 30)

	Prices (tokens per $)	Dollars in Commodity	Tokens in Comodity
Cash	**6.0** tokens per dollar	0	0.0 Tokens
Mason Money	**11.5** tokens per dollar	0	0.0 Tokens
Barnes and Noble gift card	**5.0** tokens per dollar	0	0.0 Tokens
Fandango gift card	**4.0** tokens per dollar	0	0.0 Tokens
Gap gift card	**7.5** tokens per dollar	0	0.0 Tokens
		Your total Expenditure is	0.0
			Next

Figure 1. Decision Screen

Figure 1 is an example of the decision screen. The first column contains the list of commodities. The second column contains the list of prices for each commodity (in tokens per dollar). The third column contains the quantity of commodity you will be asked to choose. This is the column you will use to make your decisions. The fourth column shows the allocation of your tokens among commodities ($Quantity\ of\ commodity*Price\ of\ commodity$).

Once you have decided what allocation of tokens you prefer, press the button **"Next"**. The computer will present you with the next decision problem or a screen asking you to wait for your final payments if you already went through 30 decision problems.

Your earnings:

Your earnings from the experiment are determined as follows. At the end of experiment, the computer will randomly select one of 30 decision problems. You will be paid according to choices you made. This means that each decision problem has the same 1 in 30 chance of being randomly selected. Note that each decision problem is independent from each other. Therefore, please pay attention to each one of them.

Once the computer randomly selects a decision problem, it will privately show you your choices (in the selected decision problem) and your payment (in terms of dollars of each commodity). As part of the check out process, you will have an opportunity to observe the experimenters imputing the amount of Mason Money and other commodities on the web. Note that e-gift cards purchased today can **only** be sent to your Masonlive e-mail account. You therefore need to provide a valid masonlive account to implement your payments.

Note that we will start conducting payments only after everyone in the room has finished the experiment. If you finish early, please remain silent and wait until everyone is done with the experiment.

If you have any questions, please raise your hand and and an experimenter will assist you in private.

Thank You and Good Luck!

INSTRUCTIONS

Thank you for participating in today's experiment. Please remain silent during the experiment. If you have any questions, please raise your hand and the experimenter will assist you in private.

This is an experiment in individual decision-making. Your earnings from the experiment will depend in part on your decisions and on chance. Your earnings will **not** depend on the decisions of other participants. Please pay careful attention to the instructions as a considerable amount of money is at stake.

Your payment in today's experiment will not be lower than $15 equivalent. This will be paid to you at the end of the experiment in private.

You will face 30 decision problems. In each decision problem, you will be given 100 tokens to be divided among 3 commodities. The three commodities are:

- **Cash**

  You can choose any (integer) dollar amount of this commodity. The amount of your choice will be paid to you at the end of experiment.

- **Mason Money**

  This is a prepaid debit program that provides a fast, safe and convenient way to make purchases on and off campus. Mason Money is accepted at all cafes and restaurants on campus and is linked to your Mason ID.

- **Barnes and Noble gift card**

  Barnes and Noble is the largest retail bookseller in the United States, and a leading retailer of content, digital media and educational products in the country.

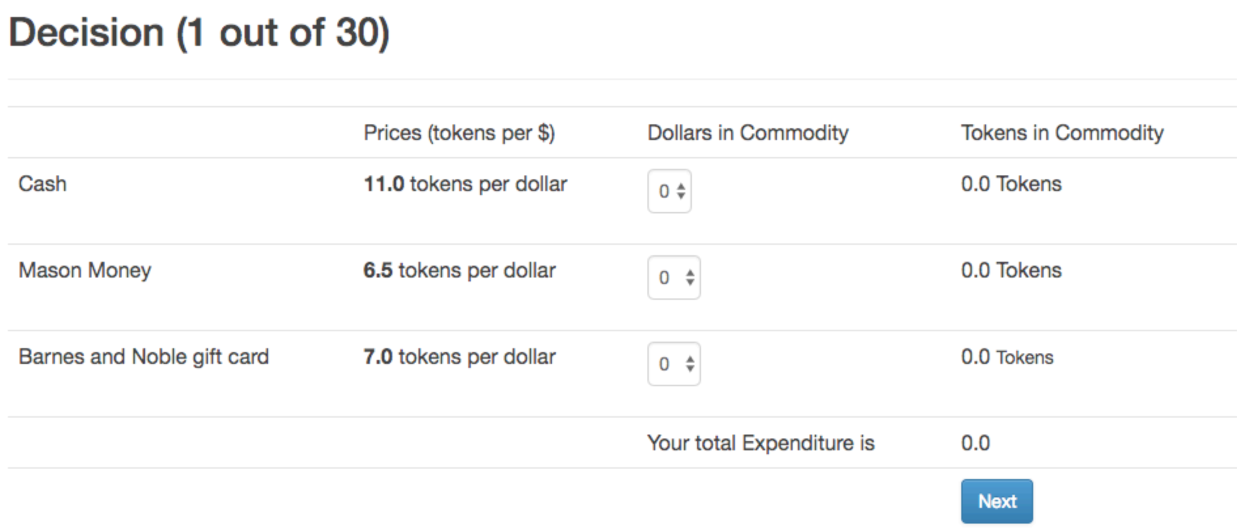
You will be asked to allocate your 100 tokens to each of these commodities for 30 different sets of prices for each commodity. Prices will range from 2.5 tokens per dollar to 15 tokens per dollar. Prices are set up in the way that you can always buy an equivalent of $15. For instance, suppose that each commodity price is 5 tokens per dollar, then you can purchase $20 in cash, or $10 in Mason Money and $10 in Barnes and Noble gift card.

Due to the restrictions set by companies on gift cards **additional restrictions** apply**:**

- If you purchase any positive amount of Mason Money, you should purchase at least $5.

- If you purchase any positive amount of Barnes and Noble gift card, you should purchase at least $10

Sample Screenshot:



Decision (1 out of 30)

	Prices (tokens per $)	Dollars in Commodity	Tokens in Commodity
Cash	**11.0** tokens per dollar	0	0.0 Tokens
Mason Money	**6.5** tokens per dollar	0	0.0 Tokens
Barnes and Noble gift card	**7.0** tokens per dollar	0	0.0 Tokens
		Your total Expenditure is	0.0
			Next

Figure 1. Decision Screen

Figure 1 is an example of the decision screen. The first column contains the list of commodities. The second column contains the list of prices for each commodity (in tokens per dollar). The third column contains the quantity of commodity you will be asked to choose. This is the column you will use to make your decisions. The fourth column shows the allocation of your tokens among commodities ($Quantity\ of\ commodity * Price\ of\ commodity$).

Once you have decided what allocation of tokens you prefer, press the button **"Next"**. The computer will present you with the next decision problem or a screen asking you to wait for your final payments if you already went through 30 decision problems.

Your earnings:

Your earnings from the experiment are determined as follows. At the end of experiment, the computer will randomly select one of 30 decision problems. You will be paid according to choices you made. This means that each decision problem has the same 1 in 30 chance of being randomly selected. Note that each decision problem is independent from each other. Therefore, please pay attention to each one of them.

Once the computer randomly selects a decision problem, it will privately show you your choices (in the selected decision problem) and your payment (in terms of dollars of each commodity). As part of the check out process, you will have an opportunity to observe the experimenters imputing the amount of Mason Money and other commodities on the web. Note that e-gift cards purchased today can **only** be sent to your masonlive account. You therefore need to provide a valid masonlive account to implement your payments.

Note that we will start conducting payments only after everyone in the room has finished the experiment. If you finish early, please remain silent and wait until everyone is done with the experiment.

If you have any questions, please raise your hand and and an experimenter will assist you in private.

Thank You and Good Luck!