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Abstract

Revealed preference theory offers a criterion for *decision-making quality*: if decisions are high quality then there exists a utility function the choices maximize. We conduct a large-scale experiment to test for consistency with utility maximization. Consistency scores vary markedly within and across socioeconomic groups. In particular, consistency is strongly related to wealth: a standard deviation increase in consistency is associated with 15-19 percent more household wealth. This association is quantitatively robust to conditioning on correlates of unobserved constraints, preferences, and beliefs. Consistency with utility maximization under laboratory conditions thus captures *decision-making ability* that applies across domains and influences important real-world outcomes.

JEL Classification Numbers: C93, D01, D03, D12, D81

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1 Introduction

Economists have long attributed heterogeneity in choices to heterogeneity in preferences, constraints, information, or beliefs. More recently, several strands of research consider heterogeneity in choices driven also by differences in decision-making ability (DMA). Different from traditional economic analysis, this literature allows that the choices that some individuals actually make may be different from the choices they would make if they had the skills or knowledge to make better decisions. This research thus takes the view that those with lower DMA may make choices of lower decision-making quality (DMQ).

The idea that people vary in their DMA, and therefore make choices of different DMQ, has intuitive appeal and important consequences for economic theory and policy. However, definitive judgement about which choices exhibit low DMQ, and which people have inferior DMA, is made difficult by twin problems of *identification* and *measurement*. The identification problem is to distinguish differences in DMA from unobserved differences in preferences, constraints, information, or beliefs. The measurement problem is to define and implement a unified measure of DMQ that applies across domains and has an economic interpretation.

The identification and measurement problems. The identification problem emerges because it is usually unclear whether those with lower DMA – as evidenced by less education, lower cognitive abilities, or less financial literacy – are making choices of lower DMQ. They might have different preferences over the same outcomes, or face different but unobserved incentives and constraints, or have different information, or hold different beliefs. The measurement problem emerges because only rarely are the relevant incentives so clear and the data quality so high, that classifying some choices as of low DMQ is straightforward and uncontroversial. More generally, a measure of DMQ is challenging to formalize, quantify, and make portable for use in a variety of choice environments. Such features of a measure are especially useful if DMA is a characteristic of a person that affects decisions in many different contexts.

Observational studies of market data, experiments in the laboratory and in the field, and surveys have all been used to provide evidence of heterogeneity in DMA (across individuals) and differences in DMQ (across decisions). Each of these methods has relative advantages, and confronts the identification and measurement problems to different degrees.

Observational studies have shown that some individuals make choices of such poor DMQ that they clearly leave "money on the table." Agarwal et al. (2009) is a prominent example. That paper provides evidence of strictly dominated choices regarding the use of credit. Importantly, research like this requires an uncommonly high-quality (administrative) dataset that makes the relevant tradeoffs very clear. The comprehensive nature of the data makes classifying some decisions as "mistakes" immediate and indisputable, and thus allows the analyst to avoid both the measurement and the identification problem. However, such administrative datasets provide information about the activity at just one retailer, or on just a few credit cards, or in just one form of saving. They thus capture only a slice of the economic activities of the individuals involved. As a result, they cannot reveal whether a lower DMQ choice represents a minor bobble in otherwise sound decision-making, or a more fundamental problem in evaluating economic choices due to lack of DMA.

Experiment- or survey-based studies take a different approach. They confront the identification problem using measures of education, cognitive and non-cognitive skills, or financial literacy as proxies for DMA. A prominent example of this research is Ameriks et al. (2003). That paper provides evidence that differences in individuals' planning abilities, rather than more standard sources of heterogeneity, explain important variation in wealth. Research of this kind relaxes the imposing data requirements of observational studies that investigate DMQ directly, but it is silent on the measurement problem. It does not seek a portable, quantitative, and economically interpretable measure of DMQ.

Our approach. We offer a new approach to the challenges posed by the identification and measurement problems. Our point of departure is a proposal to measure DMQ by the consistency of choices with economic rationality, in the sense of a consistent (complete and transitive) preference ordering. We thus take the view that if there is no utility function that choices maximize then those choices cannot be considered purposeful and, in this way, high DMQ. Adopting this standard for DMQ, we present individuals with an economic choice experiment in which we can measure the DMQ of their choices with a high degree of precision. The measure has a well-established economic interpretation and revealed preference theory tells us whether we have enough data to make it statistically useful. In addition, the analytical techniques and experimental platform are easily portable to a variety of choice problems. We can thus make domain-specific predictions and study a comparable measure of DMQ across domains. Our approach thus addresses the measurement problem. Moreover, the experiment, to the extent possible, holds information and beliefs constant within subject, and controls the relevant constraints. If DMA is defined simply as exhibiting the capacity to make choices of higher DMQ, then the approach also addresses the identification problem in the laboratory. It distinguishes individual heterogeneity in DMA from unobserved differences in preferences, constraints, information, or beliefs in this setting.

Our interest in DMQ under laboratory conditions derives, in large part, from the possibility that it reflects DMA that affects important outcomes outside the laboratory. To evaluate this possibility we implement the experiment with a large and diverse sample of subjects so we can examine the relationship between DMQ in the experiment and socioeconomic characteristics. If we find a significant correlation between DMQ and certain characteristics, this lends some credence to the idea that people with these characteristics tend to make different choices not only because they face different constraints or have different preferences, but also because they tend to have different levels of DMA. To evaluate this idea rigorously, we investigate whether our measure of DMQ from the experiment can independently explain important economic outcomes in the real world. If heterogeneity in DMA is an important source of heterogeneity in real world outcomes, and if DMQ in the experiment is a good proxy for DMA, then differences in the experiment-based measure across subjects should help explain differences in their real-world outcomes.

We conducted the experiment, through a web-based panel study, with a representative sample of Dutch-speaking households in the Netherlands. The experiment presents subjects with standard consumer decision problems that can be interpreted either as the selection of a bundle of commodities from a budget set or the allocation of an endowment between risky assets. These decision problems are presented using a graphical experimental interface that allows for the collection of a rich individual-level data set (Choi et al., 2007a).

Summary of results. Our analysis begins with a description of DMQ in the experiment by evaluating the consistency of individual behaviors with the Generalized Axiom of Revealed Preference (GARP). We assess how nearly individual choice behavior complies with GARP using standard measures of consistency that have been proposed for quantifying the extent of violations. We then move to a regression analysis of the relationship between consistency with GARP and socioeconomic characteristics. There is marked heterogeneity in the consistency scores within and across socioeconomic groups. We find that high-income and high-education subjects display greater levels of consistency than low-income and low-education subjects, and young subjects are more consistent than older subjects. In this way we provide new quantitative evidence on the question: "who is (more) rational?"

The higher levels of DMQ among high-income, high-education, and younger subjects, suggest that these groups tend to have better economic outcomes, not only because they tend to face less constraints, have more normative preferences, have more information, or hold more accurate beliefs, but also because they tend to have superior DMA. This motivates an investigation of the ability of DMQ in the experiment to explain important real-world outcomes. We chose wealth as the outcome of interest. The task of explaining wealth provides a strong test of the idea that DMQ in the experiment reflects a more general form of DMA. The test is strong because wealth is determined by countless decisions, made over time in many different settings, and involving many different tradeoffs, thus increasing our chance of rejecting a relationship. However, we find an economically large and statistically significant association between consistency in the experiment and household wealth. The point estimates indicate that, conditional on measures of current income, education, occupation, basic demographic characteristics and household structure, a standard deviation increase in the consistency score of the person who is primarily responsible for household financial matters is associated with 15-19 percent more household wealth.

As important, the estimated correlation is little changed when we condition on correlates of unobserved constraints, preferences, information, and beliefs. The goal of this robustness analysis is not to "control for everything." Instead, in the spirit of Altonji et al. (2005), we examine whether the estimated correlation is much affected by the inclusion of additional controls that, *a priori*, should be correlated with economic outcomes through their correlation with unobserved variables. If these unobservables are indeed important sources of the observed correlation between consistency and economic outcomes, then adding the controls should have a substantial effect on the estimated correlation coefficients. We interpret the economically large, statistically significant, and quantitatively robust relationship between DMQ in the experiment – the consistency of the experimental data with the utility maximization model – and household wealth as evidence of DMA that applies across choice domains and influences important real-world outcomes.

The rest of the paper is organized as follows. Section 2 describes the experimental design and procedures. Section 3 describes DMQ in the experimental data. Section 4 contains analysis of the relationship between DMQ and socioeconomic characteristics. Section 5 discusses the correspondence between wealth differentials and DMA. Section 6 provides a discussion of some related literature and Section 7 contains some concluding remarks. The paper also includes five data and technical appendices for the interested reader.[1]

2 Experimental design

2.1 Sample

The experiment uses the CentERpanel, an online, weekly, and stratified survey of a sample of over 2,000 households and 5,000 individual members. The sample is designed to be representative of the Dutch-speaking population in the Netherlands. Via the Internet, the survey instrument allows researchers to implement experiments and collects a great deal of individual demographic and economic information from its respondents. The subjects in the experiment were recruited at random from the entire CentERpanel sample. The experiment was conducted online with 1,182 CentERpanel adult members. Table 1 provides summary statistics of individual characteristics. We present the data for *participants* (completed the experiment), *dropouts* (logged in but quit the experiment) and *nonparticipants* (recruited for the experiment but never logged in). In later analysis we will control for sample selection using Heckman's (1979) model.

[Table 1 here]

2.2 Procedures

Our experimental interface was incorporated into the CentERpanel and the experiment was hosted as part of their survey. In our experiment, we present subjects with a sequence of decision problems under risk. Each decision problem was presented as a choice from a two-dimensional budget line. A choice of the allocation (x, y) from the budget line represents an allocation of points between accounts x and y (corresponding to the horizontal and vertical axes). The actual payoffs of a particular choice were determined by the allocation to the x and y accounts; the subject received the points

[1] Appendix #: http://emlab.berkeley.edu/~kariv/CKMS_I_A#.pdf.

allocated to one of the accounts x or y, determined at random and equally likely.

The procedures described below are identical to those used by Choi et al. (2007b), with the exception that the experiment described here consisted of 25, rather than 50, decision problems.[2] We also made some minor changes to accommodate the online experimental setting. Each decision problem started with the computer selecting a budget line randomly from the set of budget lines that intersect with at least one of the axes at 50 or more points, but with no intercept exceeding 100 points. The budget lines selected for each subject in different decision problems were independent of each other and of the sets selected for any of the other subjects in their decision problems. Choices were restricted to allocations on the budget constraint.[3] Choices were made using the computer mouse to move the pointer on the computer screen to the desired point and then clicking the mouse or hitting the enter key. More information and full experimental instructions, including the computer program dialog window, are available in Appendix I.

During the course of the experiment, subjects were not provided with any information about the account that had been selected in each round. At the end of the experiment, the computer selected one decision round for each subject, where each round had an equal probability of being chosen, and the subject was paid the amount he had earned in that round. Payoffs were calculated in terms of points and then converted into euros. Each point was worth €0.25. Subjects received their payment from the CentERpanel reimbursement system via direct deposit into a bank account.

3 Decision-making quality

We propose to measure DMQ by the consistency of choices with economic rationality, and we described a simple economic choice experiment in which we can measure DMQ with a high degree of precision, and separate

[2]The number of individual decisions is still higher than usual in the literature, and revealed preference analysis presented below shows the experiment provides a data set consisting of enough individual decisions over a sufficiently wide range of budget lines to provide a powerful test of consistency.

[3]Like Choi et al. (2007b), we restricted choices to allocations on the budget line so that subjects could not dispose of payoffs. In Fisman et al. (2007), each decision involved choosing a point on a graph representing a budget set that included interior allocations. Since most of their subjects had no violations of budget balancedness (those who did violate budget balancedness also had many GARP violations even among their choices that were on the budget line), we restricted choices to allocations on the budget constraint to make the computer program easier to use.

it from other sources of heterogeneity in choice. Specifically, we employ the Generalized Axiom of Revealed Preference (GARP) to test whether the finite set of observed price and quantity data that our experiment generated may be rationalized by a utility function. GARP generalizes various revealed preference tests. It requires that if allocation x^i is revealed preferred to x^j, then x^j is not *strictly* and directly revealed preferred to x^i; that is, allocation x^i must cost at least as much as x^j at the prices prevailing when x^j is chosen.[4]

If choices are generated by a non-satiated utility function, then the data must satisfy GARP. Conversely, the result due to Afriat (1967) tells us that if a *finite* data set generated by an individual's choices satisfies GARP, then the data can be rationalized by a utility function. Consistency with GARP has long been a touchstone for rationality, but it demands only a complete and transitive preference ordering. It places no restrictions on the utility function, and makes no assumptions about what is reasonable to maximize. Since it is possible to "pump" an indefinite amount of money out of an individual making intransitive decisions, consistency with GARP provides a crucial test of DMQ.

An individual's decisions may violate GARP and thus be of low DMQ for a number of reasons. First, violations of GARP can result from "trembles." Subjects may compute payoffs incorrectly, execute intended choices incorrectly, or err in other less obvious ways. Second, inconsistency can result from bounded rationality or cognitive biases such as "framing effects" and "mental accounting" (Kahneman and Tversky, 1984). The resources needed for determining optimal choices are limited. Thus, especially in complex or unfamiliar environments, the cost of computing an optimal decision can be high. Some subjects may therefore adopt simple decision rules, and this "simplification" may cause their choices to be inconsistent.[5] Third, if the data (p^i, x^i) satisfy GARP, then they can be rationalized by an outcome-based utility function $U(x_1, x_2)$. However, unobserved factors could enter

[4]Without loss of generality, assume the individual's payout is normalized to 1. The budget set is then $p_1x_1 + p_2x_2 = 1$ and the individual can choose any allocation x that satisfies this constraint. Let (p^i, x^i) be the data generated by an individual's choices, where p^i denotes the i-th observation of the price vector and x^i denotes the associated allocation. An allocation x^i is directly revealed preferred to x^j if $p^i x^i \geq p^i x^j$. An allocation x^i is revealed preferred to x^j if there exists a sequence of allocations $\left\{x^k\right\}_{k=1}^{K}$ with $x^1 = x^i$ and $x^K = x^j$, such that x^k is directly revealed preferred to x^{k+1} for every $k = 1, ..., K-1$.

[5]Consistency is also endogenous: subjects can make decisions that are consistent with GARP in a complex decision problem because they adopt simple choice rules to cope with complexity. But in that case, the "revealed" preference ordering may not be the "true" underlying preference ordering.

the utility function so the "true" underlying preference ordering is represented by a utility function $U(x_1, x_2, \omega)$ parametrized by ω. If the data (p^i, x^i) are generated by a utility function $U(x_1, x_2, \omega)$ and ω is fixed, then the data will still satisfy GARP. An example of this is the disappointment aversion model proposed by Gul (1991), where the safe allocation $x_1 = x_2$ is the reference point. If, however, ω is not fixed then subjects can exhibit "preference reversals" and the data (p^i, x^i) might not satisfy GARP (cf. Bernheim and Rangel, 2009 where ω may be time). The variable ω may also be interpreted, as in Kőszegi and Rabin (2006), as a *dynamic* reference point determined endogenously by the environment.

3.1 Consistency with GARP

Although testing conformity with GARP is conceptually straightforward, there is a difficulty: GARP provides an exact test of utility maximization – either the data satisfy GARP or they do not. We assess how nearly individual choice behavior complies with GARP by using Afriat's (1972) Critical Cost Efficiency Index (CCEI), which measures the fraction by which all budget constraints must be shifted in order to remove *all* violations of GARP. Put precisely, for any number $0 \leq e \leq 1$, define the direct revealed preference relation

$$x^i R^D(e) x^j \Leftrightarrow e p^i \cdot x^i \geq p^i \cdot x^j,$$

and define $R(e)$ to be the transitive closure of $R^D(e)$. Let e^* be the largest value of e such that the relation $R(e)$ satisfies GARP. The CCEI is the e^* associated with the data set. By definition, the CCEI is between zero and one – the closer the CCEI is to one, the smaller the perturbation of the budget constraints required to remove all violations and the closer the data are to satisfying GARP. The CCEI thus provides a summary statistic of the overall consistency with GARP, reflecting the minimum adjustment required to eliminate all violations of GARP associated with the data set.

In our experiment, the CCEI scores averaged 0.881, which implies that on average budget sets needed to be reduced by about 12 percent to eliminate a subject's GARP violations.[6] There is also marked heterogeneity in the CCEI

[6] In contrast, Choi et al. (2007b) report that 60 of their 93 subjects (64.6 percent) had CCEI scores above the 0.95 threshold and that over all subjects the CCEI scores averaged 0.954 (see Figure 1). The subjects of Choi et al. (2007b) were undergraduate students and staff at UC Berkeley, and the experiment was conducted in the laboratory. We note that the subjects of Choi et al. (2007b) were given a menu of 50 budget sets which provides a more stringent test of GARP.

scores within and across socioeconomic groups. Figure 1 summarizes the mean CCEI scores and 95 percent confidence intervals across selected socioeconomic categories. On average, high-income and high-education subjects display greater levels of consistency than lower-income and lower-education subjects. Men are more consistent than women, and young subjects tend more toward utility maximization than those who are old. The magnitudes imply that, in order to eliminate their GARP violations, low-income subjects require an average contraction of their budgets that is 3.3 percentage points larger than that of high-income subjects. The corresponding numbers for low-education subjects, females, and old subjects are 2.6, 2.4, and 5.1, respectively.[7] We will further analyze the relationship between consistency scores and socioeconomic characteristics, and address sample selection, in our regression analysis below.

[Figure 1 here]

A key advantage of the CCEI is its tight connection to economic theory. This connection makes the CCEI economically quantifiable and interpretable. Moreover, the same economic theory that inspires the measure also tells us when we have enough data to make it statistically useful. Thus this theoretically grounded measure of DMQ helps us design and interpret the experiments in several ways. In Appendix II, we provide more details on testing for consistency with GARP, discuss the power of the revealed preference tests, explain other indices that have been proposed for this purpose, and describe the related empirical literature on revealed preferences. In reporting our results, we focus on the CCEI. The results based on alternative indices are presented in Appendix III. In practice, all indices yield similar conclusions.

3.2 Beyond consistency

Stochastic dominance. Consistency with GARP requires consistent preferences over all possible alternatives, but any consistent preference ordering is admissible. In this way, we see consistency as a necessary, but not sufficient, condition for choices to be considered of high DMQ. Indeed, choices can be consistent with GARP and yet fail to be reconciled with any utility

[7] To allow for small trembles resulting from the slight imprecision of subjects' handling of the mouse, our consistency results allow for a narrow confidence interval of one point (that is, for any i and $j \neq i$, if $\left|x^i - x^j\right| \leq 1$ then x^i and x^j are treated as the same portfolio).

function that is normatively appealing. For example, consider individuals in the experiment who always allocate all points to the same account as measured by x_1. This behavior is consistent with maximizing the utility function $U(x_1, x_2) = x_1$ and would generate a CCEI score of one. Such preferences are, however, hard to justify in this setting because for many of the budget sets that a subject faces, always allocating all points to the same account means allocating all points to the more expensive account, a violation of monotonicity with respect to first-order stochastic dominance (FOSD). Violations of FOSD may reasonably be regarded as errors, regardless of risk attitudes – that is, as a failure to recognize that some allocations yield payoff distributions with unambiguously lower returns. FOSD is thus a compelling criterion for DMQ and is generally accepted in decision theory (Quiggin, 1990, and Wakker, 1993).

To measure the extent of GARP *and* FOSD violations (for a given subject), we can combine the actual data from the experiment and the *mirror-image* of these data, compute the CCEI for this combined data set, and compare that number to the CCEI for the actual data.[8] The CCEI score for the combined data consisting of 50 observations can be no bigger than the CCEI score for the actual data. For example, recall the preferences represented by $U(x_1, x_2) = x_1$, where the individual always allocates all points to x_1. Such choices are perfectly consistent with GARP, but they generate severe violations when combined with their mirror-images.[9] Similarly, any decision to allocate fewer points to the cheaper account will generate a violation of the Weak Axiom of Revealed Preference (WARP) involving the mirror-image of this decision. On average, the CCEI score is 0.733 for the combined data compare to 0.881 for the actual data. In our econometric analysis below, we use both the CCEI scores for the actual data set and for the combined data set. In Appendix IV, we assess how closely individual choice behavior complies with FOSD using an alternative measure based on expected payoff calculations. Replacing the CCEI score for the combined data with this measure of FOSD violations in the econometric analysis below yields similar conclusions.

Risk attitudes. Our experimental task delivers measures of both DMQ and (risk) preferences from a single realm of decision-making. We summa-

[8] The data generated by an individual's choices are $\left\{\left(p_1^i, p_2^i, x_1^i, x_2^i\right)\right\}_{i=1}^{25}$ and the mirror-image data are obtained by reversing the prices and the associated allocation for each observation $\left\{\left(p_2^i, p_1^i, x_2^i, x_1^i\right)\right\}_{i=1}^{25}$.

[9] Of the 1,182 subjects in the experiment, only 29 subjects (2.5 percent) almost always allocated all points to one of the assets by choosing the same endpoint of the budget line.

rize an individual's attitudes toward risk with a single statistic: the fraction of total points he allocated to the cheaper account. We choose this measure because, in each problem that a subject faces, each account is equally likely to be chosen and the budget set is drawn from a symmetric distribution. Thus, the only behavior consistent with infinite risk aversion is always allocating the points equally between the two accounts. Conversely, always allocating all points to the cheaper account is the behavior that would be implied by risk neutrality. More generally, subjects who are less averse to risk will allocate a larger fraction of points to the cheaper account. Like the revealed preference tests, an advantage of this measure is that it is non-parametric. It measures attitudes toward risk without making assumptions about the parametric form of the underlying utility function.[10] Figure 2 displays the mean fraction of points allocated to the cheaper account and 95 percent confidence intervals across the socioeconomic categories. We note that there is considerable heterogeneity in risk attitudes across categories, which is characteristic of all these data, and that risk attitudes and CCEI scores are effectively uncorrelated ($\rho = 0.113$).[11,12]

[Figure 2 here]

4 Decision-making quality and socioeconomics

We next perform what is, to our knowledge, the first analysis of the correlation between DMQ – the consistency of the experimental data with GARP – and socioeconomic characteristics. Table 2 below presents the results of the econometric analysis. In column (1), we present estimates

[10] In parametric estimation, beyond the scope of this paper, we find that the choice data of many subjects are well explained by a preference ordering in which the indifference curves have a kink at the 45 degree line, corresponding to an allocation with a certain payoff. One interpretation of this preference ordering is the disappointment aversion model proposed by Gul (1991). This finding corroborates the results in Choi et al. (2007b) with undergraduate students.

[11] As Figure 2 shows, our individual-level measures of risk aversion are higher than the measures reported in Choi et al. (2007b), but they are within the range of estimates from recent studies (see Choi et al., 2007b, for a discussion of these studies).

[12] The seminal paper by Holt and Laury (2002) also reports substantial low-stakes risk aversion in the lab, as does Andersen et al. (2007) in the field. Risk aversion over moderate stakes contradicts the validity of Expected Utility over wealth (Rabin, 2000, and Rabin and Thaler, 2001). We emphasize that GARP does not imply the Savage (1954) axioms on which Expected Utility is based and Expected Utility need not be assumed to investigate the DMQ of choice under uncertainty.

with the CCEI scores for the actual data set using ordinary least squares.[13] The results show significant correlations. We obtain statistically significant coefficients in nearly all socioeconomic categories, ranging in absolute values from about 0.025 to just over 0.050. Most notably, females, low-education, low-income, and older subjects on average "waste" as much as 2.4, 2.6, 3.3, and 5.1 percentage points more of their earnings, respectively, by making inconsistent choices. In columns (2) we repeat the estimation reported in columns (1) using the CCEI scores for the combined data set. The two scores are highly correlated ($\rho = 0.645$) and, unsurprisingly, the results are qualitatively similar.

[Table 2 here]

The preceding analysis is based on the non-randomly selected subsample of participants. The lack of observations on panel members who chose not to participate or did not complete the experiment creates a missing data problem. We evaluate sample selection bias in our econometric analysis using Heckman's (1979) method. Our exclusion restriction involves the number of completed CentERpanel questionnaires out of the total invitations to participate in the three months prior to our experiment. This variable enters the participation equation but, we assume, is conditionally uncorrelated with the CCEI (see, Bellemare et al., 2008). To economize on space, the estimation results are reported in Appendix V. The estimated parameters from the OLS and the sample selection estimations are virtually identical. We interpret these results to indicate that self-selection is not importantly driving the results.

5 Wealth differentials and decision-making ability

The preceding analysis shows higher CCEI scores among high-income, high-education, and younger subjects. This finding suggests that these groups may have better economic outcomes, not only because they face fewer constraints or have more normative preferences, but also because they tend to have superior DMA. This finding thus motivates an investigation of the correspondence between the CCEI scores and important economic outcomes in the real world. If heterogeneity in DMA is an important source of heterogeneity in economic outcomes, and if DMQ in the experiment as

[13] To test for a potential misspecification, we used Ramsey's (1969) RESET test by adding the squared and cubed fitted values of the regression equation as additional regressors, and found no evidence of misspecification (p-value = 0.3098).

measured by the CCEI scores is a good proxy for DMA, then differences in the CCEI scores across subjects should independently explain differences in their real-world outcomes. We focus on household wealth as the real-world economic outcome of interest. As we argued, the investigation of wealth offers a strong test of the idea that DMQ in the experiment captures DMA. Wealth is also of special interest because Bernheim et al. (2001) and Ameriks et al. (2003) show substantial differences in wealth even among households with very similar lifetime incomes, and provide evidence that differences in DMA drive wealth differentials.

The CentERpanel collects information about wealth on an annual basis. Panel members are asked to identify a financial respondent who is "most involved with the financial administration of the household." All panel members age 16 and older respond to questions about the assets and liabilities that they hold alone. The financial respondent also provides information about assets and liabilities that are jointly held by more than one household member. The inventory covers checking and saving accounts, stocks, bonds and other financial assets, real estate, business assets, mortgages, loans, and lines of credit. Our analysis focuses on non-pension household wealth, calculated by summing net worth over household members and taking the household's average over 2008 and 2009. The 703 households with wealth data and a CCEI score from the household's financial respondent had an average household wealth of €164,130. Percentile values (in thousands of Euros) are provided below.[14]

Min	1	5	10	25	50	75	90	95	Max
-180.7	-68.2	-4.8	0.0	10.8	93.0	242.1	523.8	955.6	3984.2

Our primary analysis of wealth proceeds in three steps:

[1] We first establish the correlation between the CCEI and household wealth by estimating regressions of the log of household wealth on socioeconomic variables (including a flexible function of age), the log

[14] The CentERpanel data do not include information on pension wealth. Nearly all of the Dutch population is covered by the public pension system whose benefits are a relatively simple function of family structure. A large majority of workers is also covered by private pensions associated with their employment. Nearly all of these employment-based plans are defined benefit, the vast majority of which pay benefits as a function of earnings. Conditioning on family structure and earnings should, therefore, do much to control for the incentives these pensions create for non-pension wealth accumulation. See Alessie and Kapteyn (2001) and OECD (2009) for details about the pension systems in the Netherlands. While it is a necessity, studying non-pension wealth has the advantage of better isolating discretionary wealth accumulation.

of household contemporaneous income, and the consistency score of the financial respondent in the household.

[2] We demonstrate that this correlation is quantitatively robust to the inclusion of additional controls that, *a priori*, should be correlated with wealth through their correlation with unobserved variables. If these unobservables were important sources of the observed correlation, then adding the controls should have a substantial effect on the estimated correlation coefficients (cf. Altonji et al., 2005.)

[3] We finally show that alternative measures of DMQ from the experiment and DMA from the survey are not substitutes for the CCEI. The available alternatives either have no independent power to predict wealth, or are not well-correlated with consistency with GARP.

Step 1: Establishing the correlation between CCEI and wealth

In our baseline specification, the sample size drops from 703 to 517 households (73.5 percent). This decline derives largely from three sources. First, 54 households (7.7 percent) have negative or missing household income in 2008, and 74 households (10.5 percent) have negative wealth and thus a missing dependent variable. Second, younger households face incentives to hold less wealth as they borrow in order to invest or to smooth lifetime consumption. With that in mind, we drop the 49 households (7.0 percent) whose financial respondent is less than 35 years old. Finally, to reduce the importance of extreme outliers, we drop the seven households that represent the top and bottom half of one percent of the wealth distribution and the bottom half of one percent of the CCEI distribution. Two additional households are dropped due to missing data on education. Our basic estimation results are reported in Table 3 below.

Baseline. In column (1), we present estimates from our baseline specification using the sample of 517 households described above. The point estimate of 1.35 for the coefficient on the CCEI indicates that a standard deviation increase in the CCEI score of the household's financial respondent is associated with 18 percent more household wealth. As one might expect from a relatively small sample of data on self-reported wealth, the standard error on this point estimate is fairly large. Nevertheless, we can reject a null hypothesis of no relationship at the 5 percent level (p-value=0.017) with standard errors robust to heteroskedasticity.

Lifecycle. In column (2), we repeat the estimation reported in column (1) with the sample not restricted to households with financial respondents who are at least 35 years old. Using the entire analysis sample, we find that the point estimate on the CCEI is somewhat smaller, so a standard deviation increase in the CCEI score of the household's financial respondent is associated with about 15 percent more household wealth. The standard error on this point estimate implies that we can reject a null hypothesis of no relationship with considerable confidence (p-value=0.038) but we cannot reject a null hypothesis that the point estimates of the coefficient on the CCEI reported in columns (1) and (2) are the same.

Levels. The log specification in column (1) and (2) excludes households with negative wealth, and may also cause small differences at positive but very low levels of wealth to have large effects on point estimates. To evaluate the sensitivity of the results to the log specification, in column (3) we estimate the regression in levels (of wealth and income) for the sample age 35 and older. We again see an economically large association between the CCEI and levels of wealth, though this relationship is estimated somewhat less precisely; the coefficient on the CCEI is significant only at the 10 percent level (p-value=0.054).

[Table 3 here]

Step 2: Assessing the robustness of the correlation

We find an economically large and statistically significant correlation between the financial respondent's CCEI score in the experiment and household wealth. This lends a basic level of support to the idea that our measure of DMQ from the experiment can proxy for DMA that applies across multiple real world choice domains. However, the correlation between the CCEI and wealth may not reflect DMA, but instead be due to a correlation between the CCEI and other standard, but so far unobserved or misspecified, sources of heterogeneity in choice that affect wealth.

To address this issue of identification and interpretation, we evaluate the robustness of the correlation with respect to the inclusion of additional controls. This analysis does not seek the impossible goal of "controlling for everything" that might influence wealth. Instead, in the spirit of Altonji et al. (2005), we examine whether the conditional correlation we see between CCEI and wealth in the basic specifications is much affected by the inclusion of additional controls that, *a priori*, should be correlated with wealth through their correlation with unobserved or misspecified variables.

Constraints. We begin by investigating the correlation of the CCEI with unobserved or misspecified constraints that affect the accumulation of wealth. The estimation results are reported in Table 4 below. In standard lifecycle models, wealth at a given age is a function of the constraints imposed by the path of income over a lifetime. There is a variety of reasonable specifications for a wealth regression, and our baseline specification reported in Table 3 above is an especially simple benchmark. In column (1) of Table 4, we assess the importance of the baseline linear-in-contemporaneous-income specification by allowing income to enter in the form of a cubic. We see virtually no change in the point estimate of the coefficient on the CCEI. We thus find no evidence that the simple specification of contemporaneous income drives the estimated relationship between the CCEI and wealth.

Another concern is that contemporaneous income is measured with error and the estimated coefficient on this variable is therefore biased toward zero. The bias of this estimate then biases estimates of the coefficients on other variables, including the CCEI. Standard lifecycle models predict constant saving rates across lifetime income groups, and thus a unit elasticity of wealth with respect to income (Dynan et al., 2004). If contemporaneous income is a good proxy for lifetime income, then these theories predict the coefficient on the log of contemporaneous income should equal one in the baseline specification. In column (2), we impose this restriction and see virtually no change in the point estimate of the coefficient on the CCEI.[15] There is thus no evidence that measurement error in contemporaneous income drives the main result.

A related concern is that contemporaneous income is a poor proxy for the *path* of lifetime income, and unobserved aspects of that path are correlated with the CCEI.[16] We can evaluate this concern with some of the limited panel data available on household income. To strike a balance between capturing more income information and maintaining reasonable sample sizes, we go back five years and use household income information for every other year.[17] In column (3) of Table 4, we repeat the baseline specification re-

[15] Brown (1976) shows that if theory makes a prediction about the coefficient on a variable that is measured with error then restricting that coefficient to take on the value predicted by theory will reduce the bias on the other coefficients being estimated.

[16] Scholz et al. (2006) show that by using detailed data on household-specific earnings, the optimal decision rules from a life-cycle model can account for more than 80 percent of the cross-sectional variation in wealth. They thus argue, in contrast to Bernheim et al. (2001) and Ameriks et al. (2003), that heterogeneity in DMA is not necessary to explain much of the heterogeneity in wealth.

[17] The CentERpanel has been operating since 1993. However, income data for most households who responded to the 2009 survey and completed our experiment do not go

ported in column (1) of Table 3, this time restricting attention to the 449 households (86.8 percent) for whom we have household income data from 2004 and 2006, as well as from 2008. In this smaller sample, the point estimate on the CCEI remains economically large and statistically different from zero (p-value=0.004). In column (4), we add controls for the log of household income in 2004 and 2006. As a result, the magnitude of the coefficient on the CCEI declines only slightly (by 0.037). We interpret this to indicate that, while some of the correlation between the CCEI and wealth may be attributable to a correlation between the CCEI and unobserved past income, the available CentERpanel data on income provide little evidence that this is the case.

An alternative approach is to take completed education as a proxy for lifetime income. All of our specifications so far include indicators for each level of education completed. It may be, however, that unobserved aspects of education, such as the quality of schooling, are correlated with unobserved elements of lifetime income which are, in turn, correlated with the CCEI score in the experiment. If so, and if these unobserved constraints are important sources of the observed correlation between CCEI and wealth, then conditioning on completed education should have a substantial effect on the estimated coefficient on the CCEI. In column (5) of Table 4, we repeat the baseline specification reported in column (1) of Table 3 after omitting the controls for the education of the financial respondent. Comparing the estimates from these two specifications, we see that removing the education controls increases the estimated coefficient on the CCEI only modestly (by 0.090). In this way, we find little evidence that unobserved aspects of education are driving the correlation between the CCEI and wealth.

[Table 4 here]

Preferences. We have evaluated whether the correlation between the CCEI and wealth is due to a relationship between the CCEI and unobserved or misspecified income constraints. The results on education, which we took to proxy for unobserved income but could also proxy for attitudes toward risk and time, suggest that the relationship between the CCEI and unobserved preferences is unlikely to play an important role. Nevertheless, we next turn to analyze the possibility that the correlation between the CCEI and wealth is driven by a relationship between the CCEI and unobserved preferences that determine wealth. The estimation results are reported in Table 5 below.

back nearly that far. In cases where we have two out the three income measures, we use linear extrapolation to fill in the third.

Our experimental task delivers individual-level measures of both DMQ and risk preferences from a single realm of decision-making. In column (1) of Table 5 we add to the baseline specification reported in column (1) of Table 3 a control for risk attitudes by including a nonparametric measure from the experiment discussed above – the average fraction of points the financial respondent allocated to the cheaper account.[18] The point estimate on this *quantitative* measure indicates that risk tolerance in the experiment is negatively associated with wealth. The coefficient is economically large – a standard deviation increase in the fraction placed in the cheaper account is associated with about seven percent less household wealth – but imprecisely estimated. We cannot reject a null hypothesis of no relationship (p-value=0.282) or a null of an economically large and positive relationship. Given that risk attitudes and CCEI scores in the experiment are weakly correlated ($\rho = 0.113$), it is unsurprising that the inclusion of this control leaves the point estimate of the coefficient on the CCEI little changed.

It may be, however, that risk attitudes that influence wealth are not well-correlated with risk preferences revealed over the small stakes of the experiment. If so, *qualitative* measures of risk tolerance taken from the CentERpanel survey instead of the experiment, may do better. In column (2), we evaluate this possibility by also including a normalized measure of risk-taking in investments.[19] To preserve sample size, we also include a variable to indicate whether the respondent provided a complete answer to these questions. The results reinforce those from the previous specification. The point estimate of the coefficient on the qualitative risk tolerance measure is economically small, but imprecisely estimated. As important, the inclusion of these qualitative measures of risk attitudes leaves the estimated coefficient on the CCEI virtually unchanged. We thus find no evidence that these qualitative measures of risk attitudes from the survey are better able to capture unobserved preferences, correlated with the CCEI, that influence

[18] To avoid the influence of extreme outliers, and to place this variable on more equal footing with the CCEI, we also estimated a specification that omited the top and bottom half of one percent of the distribution of this risk attitude measure, a total of six households. The results are qualitatively similar.

[19] The CentERpanel survey contains six statements related to investment risk and return such as “I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns,” and “I want to be certain my investments are safe.” Respondents are asked to evaluate the accuracy of these statements as descriptions of themselves on a seven point scale. We sum the responses for each respondent, when necessary re-ordering them so that higher scores reflect greater risk tolerance. We then normalize the scores to have sample mean 0 and standard deviation 1.

wealth.

In a final effort to evaluate the importance of a correlation between the CCEI and unobserved preferences, in column (3) we add to the list of controls a conscientiousness measure from the "Big Five" test used for personality research in psychology.[20] Again, to preserve sample size, we also include a variable to indicate whether the respondent completed the conscientiousness questions. If not, we set their score to mean of the sample (zero). The magnitude of the coefficient on conscientiousness is large. A standard deviation increase in conscientiousness is associated with about nine percent more wealth. The standard error on the conscientiousness coefficient is also relatively large, however, and we cannot reject a null hypothesis of no correlation. Most important, adding the control for conscientiousness has almost no effect on the coefficient on the CCEI. Thus we again find no evidence that the relationship between the CCEI and wealth is driven by a correlation between the CCEI and unobserved preferences that influence wealth.

Beliefs. Standard lifecycle models predict that beliefs, such as expectations for longevity, income, or asset returns, should affect household wealth levels. The CentERpanel collects relatively little information about respondents' beliefs, but the survey does ask questions about expected longevity. We can therefore use these data to evaluate the extent to which the correlation between the CCEI and wealth accumulation is attributable to a correlation between the CCEI and some unobserved beliefs that influence wealth. To strike a balance between capturing more information and maintaining the sample sizes, we consider a measure of longevity expectations based on the question answered by the largest number of respondents.[21]

[20] The other Big Five personality traits are openness, extraversion, agreeableness, and neuroticism. Among the Big Five, conscientiousness has the strongest correlation with economic success (see, for examples, Barrick and Mount, 1991, and Tett et al., 1991). Conscientious people are described as "thorough, careful, reliable, organized, industrious, and self-controlled" (Duckworth et al., 2007). These terms suggest more patience, less risk tolerance, and less taste for leisure. Conscientiousness may thus proxy for unobserved preferences that influence wealth. The CentERpanel survey contains 10 statements related to conscientiousness. The statements include: "I do chores right away," "I am accurate in my work," among others. Respondents are asked to evaluate the accuracy of these statements as descriptions of themselves on a five point scale. For each respondent, we sum his or her responses to the 10 statements, and then normalize the scores to have sample mean 0 and standard deviation 1. When necessary, we re-ordered the responses so that higher scores reflect greater conscientiousness. Simultaneously adding other measures from the Big Five yields the same conclusion. We omit those results for the sake of brevity.

[21] The question answered by the largest number of respondents asks "How likely is it

In column (4) of Table 5, we repeat the baseline specification reported in column (1) of Table 3, this time restricting attention to the 414 households (80.0 percent) for whom the financial respondent answered this question about longevity. In this smaller sample, the point estimate of the coefficient on the CCEI remains economically large, though a larger standard error reduces the statistical significance (p-value=0.053). In column (5), we add the control for longevity expectations. This measure, itself, has little power to predict wealth levels and including it increases the estimate of the coefficient on the CCEI very slightly (by 0.023). Thus, while we have limited ability to explore this issue with available data, we find no evidence that a relationship between the CCEI and unobserved beliefs drives the correlation between the CCEI and wealth.

[Table 5 here]

Step 3: Evaluating laboratory and survey-based alternatives to the CCEI

We have found an economically large, statistically significant, and quantitatively robust correlation between the CCEI scores in the experiment and wealth. This lends credence to the idea that DMA, that is important outside the experiment, affects DMQ in the experiment as measured by the CCEI. We next evaluate whether alternative laboratory- and survey-based measures can substitute for the CCEI for the purposes of explaining wealth. Measuring DMQ by consistency with GARP has strong theoretical and methodological justifications, but augmenting GARP with additional, normative criteria might better capture DMQ. It is also possible that, while lacking in theoretical foundations, other proxies for DMA are so well-correlated with the CCEI that they may serve as substitutes for the CCEI. This would be especially useful if the other proxies are readily available on surveys or in administrative datasets. The estimation results are reported in Table 6 below.

Stochastic dominance. We begin with consideration of a stronger notion of DMQ derived from our experiment. In column (1) of Table 6 we repeat the estimation of the baseline specification reported in column (1) of Table

that you will attain (at least) the age of 80?" Responses are recorded on a scale from 0 to 10, and respondents are instructed to interpret 0 to mean "no chance at all" and 10 to mean "absolutely certain."

3 after adding the CCEI scores for the combined data set (combining the actual data from the experiment and the mirror-image data). As explained above, this test of DMQ is stronger because it demands both consistency with GARP and FOSD. We find no evidence that, conditional on the CCEI score from the actual data, the CCEI score for the combined data set has an independent relationship with wealth. Adding the CCEI for the combined data set as a regressor has only a modest effect on the point estimate of the coefficient on the CCEI, though the standard error on this estimate increases. The point estimate of the coefficient on the CCEI for the combined data set is small, but imprecisely estimated. These results are consistent with the idea that the CCEI for the combined data set, while requiring a compelling and generally accepted notion of DMQ, merely represents a noisier measure of the aspects of DMA captured by the CCEI scores for the actual data set.

Trembling. von Gaudecker et al. (2011) conducted risk experiments with CentERpanel members using a multiple price list design (Andersen et al., 2006). They estimated a flexible parametric model that includes an individual "trembling" parameter ω_i measuring "the propensity to choose randomly rather than on the basis of preferences." von Gaudecker et al. (2011) conclude that "while many people exhibit consistent choice patterns, some have very high error propensities." That parameter can be interpreted as a measure of DMQ as it captures the degree to which an individual's choices are consistent both with rationality and with some assumptions about the functional form of utility. This contrasts the CCEI, which makes no assumptions about the structure of preferences. The CCEI and the "trembling" parameter of von Gaudecker et al. (2011) are only moderately correlated ($\rho = 0.178$) in the overlapping sample of 624 subjects (43.9 percent) who participated in both experiments. As a result, we can gain some insight into the relationship between wealth and consistency with the utility-maximizing model *versus* consistency with a class of utility functions commonly employed in the empirical studies.

In column (2) of Table 6, we repeat the estimation of the baseline specification reported in column (1) of Table 3, this time restricting attention to the 326 households (63.1 percent) with a financial respondent who participated in both experiments.[22] In column (3) we add to the list of regressors a variable equal to $(1-\omega_i)$ in von Gaudecker et al. (2011). The point estimate of the coefficient on this parameter is large – a standard deviation increase

[22] To place the two measures on more equal footing, we trim the lowest one half of one percent of the distribution of each of the measures (two obervations each) in the overlapping sample.

is associated with 17 percent more household wealth – and we can reject a null hypothesis of no relationship at the 10 percent confidence level (p-value=0.057). The estimated coefficient on the CCEI is reduced somewhat when we include this estimate, but remains economically large and statistically significant at the 10 percent confidence level (p-value=0.083). There are many possible reasons for the differences in these two measures and their relationship to wealth – they are based on different methods, derived from different designs, and elicited in different experiments. Intriguingly, however, the results suggest substantial differences between DMQ measured by the restrictions imposed by the utility-maximization model and additional restrictions imposed by various hypotheses concerning functional structure. This is an interesting avenue for future work with more data on both measures.

Cognitive ability. Tests of cognitive ability (IQ) might also capture aspects of DMA (cf. Dohmen, et al., 2010.) It is therefore useful to investigate the correlation between IQ and the CCEI. If the CCEI and IQ were very well-correlated, then analysts interested in measuring DMA might be able to replace the revealed preference tests with one of the many IQ tests and, in some circumstances, the conceptual distinctions between the measures would have little practical import. It certainly seems likely that the capacity to make choices of high DMQ draws on skills of analysis and perception that also improve IQ test scores. But, if the goal is to isolate the influence of these skills on DMA, rather than on constraints, information, or beliefs, are the CCEI and IQ scores substitutes?

Many IQ tests are precluded from wide use by intellectual property rights or are impossible to implement in Internet panels. The CentERpanel has not implemented any of the well-known and wide-ranging IQ instruments. However, in connection with our and other researchers' projects, the CentERpanel asked a sample of respondents to complete Frederick's (2005) Cognitive Reflection Test (CRT) and a brief Raven's Progressive Matrices Test.[23] We omit the Raven's test because it generated effectively no variation in responses. Among the 467 subjects who completed the CRT and participated in our experiment, the correlation between the CCEI and the

[23] The CRT consists of three questions. Each question is designed to have an intuitive, but incorrect, answer. The intuitive answer tends to spring to mind and then require reflection in order to dismiss. One question asks "A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?" Here the intuitive answer is $0.10, but the correct answer is $0.05. Frederick (2005) shows that this test is well correlated with a 50-question test of general cognitive ability, as well as tests of achievement such as the Scholastic Achievement Test (SAT).

CRT is positive, but the variables are far from collinear ($\rho = 0.193$).[24] To assess the predictive content of each measure, in column (4) in Table 6 we add the number of questions answered correctly in the CRT to the baseline specification. To preserve sample size, we also include a variable to indicate whether a CRT score was available for the household's financial respondent. For those who had no score, we substitute the mean of the distribution of the rest of the sample.

The point estimate of the coefficient on the CRT is economically large – answering one more of the three questions on the CRT correctly is associated with about 12 percent more wealth – and statistically significant at the 10 percent level (p-value=0.094). Adding this measure, and the missing indicator, to the basic specification reduces the estimated coefficient on the CCEI somewhat, but about a fifth of the reduction is due to the inclusion of the indicator for a missing CRT score. These results suggest that the CRT captures some DMA related both to DMQ in the experiment and wealth accumulation. The findings also indicate, however, that this measure of cognitive ability cannot be used as a simple substitute for the CCEI for the purposes of explaining wealth.[25]

[Table 6 here]

The sources of correlation between CCEI and wealth

We found an economically large and statistically significant correlation between household wealth and the financial respondent's CCEI score in the experiment. We saw that this correlation is robust to the inclusion of controls for unobserved constraints, preferences, and beliefs, and that alternative measures of DMQ or DMA elicited in an experiment or a survey are not substitutes for the CCEI. With these results in mind, we now turn to account for the sources of the correlation by investigating the relationship between the CCEI and the details of household saving allocations. Our goal

[24] This result echoes Burks et al. (2009) who find a correlation of approximately 0.22 between IQ and monotonicity (measured by more than one switch point in multiple price list experiments regarding risk and time tradeoffs).

[25] Perhaps related to CRT and the tendency to reflect upon choices, adding a control for subjects' response times in the experiment has virtually no effect on the coefficient on the CCEI. This is expected given the modest unconditional correlation between the CCEI scores and response times ($\rho = -0.075$). We also cannot reject a null hypothesis of no correlation between the response time and wealth. These results are omitted in the interest of brevity.

is to better understand which important real-world decisions cause those who appear to have better DMA to accumulate more wealth. These estimation results are reported in Table 7.

Portfolio. In columns (1)-(6) of Table 7, we present estimates that relate the CCEI score of the household's financial respondent to whether the household has a checking account, a savings account, owns stocks, and the fraction of the household's wealth held in each of these assets. To reduce the importance of extreme outliers, in all specification we drop households whose fraction of wealth in the relevant category (checking, saving, stocks, housing) is less than -0.15 or greater than 1.15. The results provide some evidence that, conditional on household characteristics, contemporaneous income, occupation and education level, households with financial respondents with higher CCEI scores put less of their wealth in low-risk and low-return assets such as checking and savings accounts. The coefficients on the CCEI in columns (2) and (4) are modest in magnitude but statistically significant at the 10 percent level (p-values of 0.083 and 0.095, respectively). The results also provide some evidence that individuals with higher CCEI scores are somewhat more likely to participate in the stock market, though this relationship is not statistically distinguishable from zero.

Housing. Finally, the coefficients on the CCEI in columns (7) and (8) show economically substantial and statistically significant correlations between the CCEI and decisions regarding home ownership. Households with financial respondents with higher CCEI scores are more likely to own a home and they put a larger fraction of their household's wealth in a home. A standard deviation increase in the CCEI of the financial respondent is associated with an increase of 0.047 in the probability of owning a home. Similarly, a standard deviation increase in the CCEI is associated with an increase of 0.043 in the fraction of wealth held in housing. The tendency for those with higher CCEI scores to own a home and put more of their wealth in housing is especially interesting given the favorable tax treatment of owner-occupied housing in the Netherlands, which gives home ownership an important advantage over renting and, other things equal, means wealth placed in mortgaged housing pays a substantial premium.[26] So long as housing supply is somewhat elastic, and thus the incidence of these tax benefits

[26] About 69 percent of households in the sample own a home, and the average fraction of wealth held in housing is approximately 54 percent. In the Netherlands, assets held in owner-occupied housing are not subject to the usual capital income tax. If they were, four percent of housing value would be treated as implicit income and taxed at 30 percent. Instead, imputed rent is presumed to be very low (0.55 percent of housing value), is subject

are shared between buyers and sellers, this suggests that owning a home and placing more wealth in mortgaged housing are often high DMQ financial choices. If so, the positive correlation between the CCEI and these decisions is what we would expect if the CCEI captured a general tendency toward higher (financial) DMA.

[Table 7 here]

6 Related literature

This paper is primarily concerned with a relatively new empirical literature that adds variation in DMA to the standard sources of heterogeneity in economic choices. Different from traditional economic analysis, this literature allows that, even if they had all relevant information and knew what they wanted to achieve with their decisions, individuals might not have the DMA to identify and make the choices that best meet their objectives. Prior research in this vein can be categorized by method: some is strictly observational, the rest is experimental or survey-based.

The strictly observational studies of market data have the advantage of observing real-world decisions, sometimes with high stakes. These studies make an *a priori* judgement about which choices exhibit DMQ and use high-quality administrative data in which the DMQ of choices "speaks for itself." The DMQ of choices is judged by the amount of money they "leave on the table." The analyst arguably observes all relevant incentives and constraints, so which choices are of low DMQ is directly evident. Low DMQ choices cannot be attributed to unobserved constraints or preferences, because no such constraints or (remotely sensible) preferences could reconcile these choices. For example, Agarwal et al. (2009) show a U-shaped age pattern in the frequency of dominated choices regarding the use of credit (especially the transfer of balances among credit cards), with both relatively young and old consumers more prone to error. Other prominent examples of strictly observational studies of DMQ focus on other "slices" of the economic activities of the individuals involved: Miravete (2003) on cell phone calling

to the progressive tax on labor income, and that tax is not due unless the household claims a deduction for mortgage interest. Nominal mortgage interest is, in turn, fully deductable from taxable income. Thus, for purposes of federal taxation, housing assets underwritten by a mortgage will typically pay a negative rate of return. In this way, according to van Ewijk et al. (2007), the Netherlands offers by far the most favorable tax treatment of owner occupied housing in Western Europe.

plans, Choi et al. (2011) on employer-sponsored saving, Ketcham et al. (2012) on health insurance, and Lacetera et al. (2012) on car purchases.[27]

In contrast, experiment- or survey-based studies do not measure DMQ directly, so they are silent on the measurement problem, but they confront the identification problem by seeking proxies for DMA. These proxies include measures of education, cognitive and non-cognitive skills, and financial literacy. These studies often focus only on describing the correlation between these DMA proxies and economic choices or outcomes. Restricting attention just to financial decision-making, this literature includes, among others, Lusardi and Mitchell (2007) who document very low levels of financial planning, financial literacy, and a positive correlation between literacy, financial planning and wealth; Fang et al. (2008) who find that, rather than measures of risk preferences, cognitive functioning stands out as a significant predictor of Medigap purchase. Agarwal and Mazumder (2013) correlate proxies of DMA, namely mathematical and non-mathematical cognitive tests, with making low DMQ financial decisions involving the use of credit.[28] Other studies use instrumental variables (IV) or experimental interventions to estimate the causal effect of DMA on economic choices or outcomes. In addition to Ameriks et al. (2003), other prominent examples of research in this vein include Bernheim and Garret (2003) and Duflo and Saez (2003) who study the effect of employer-based financial education on saving.

Our approach follows the strictly observational studies by defining DMQ and measuring it directly. Different from that literature, we define DMQ by the consistency of choices with GARP, and we measure it by the extent

[27] Echenique et al. (2011) take a different approach to observational study of DMQ. They measure consistency with revealed preference conditions in individual-level data on grocery store expenditures. Their measure is based on the idea that an individual who violates GARP can be exploited as a "money pump." We refer the interested reader to Appendix II for the construction of the money pump index. Echenique et al. (2011) conclude that "the hypothesis of consumer rationality cannot be rejected." Such consumption data can, however, lack power to reject violations of GARP (Blundell et al., 2003, 2008). The power of the test depends on the range of prices consumers face (the frequency with which budget lines cross) and the number of choices each consumer makes.

[28] Special attention has been paid in this literature to older populations. This emphasis derives, in part, out of a concern about decreasing DMA later in life. The papers in the November 2010 issue of the *Economic Journal* (Volume 120, Issue 548) offer nice reviews: Banks (2010) summarizes research on the relationships between cognitive function, financial literacy and financial outcomes at older ages; Smith et al. (2010) and Banks et al. (2010) show that wealth and retirement saving patterns are associated with numerical and other cognitive abilities at middle and older ages; and Van Den Berg et al. (2010) and Jappelli (2010) explore causes of the differences in cognitive function and financial literacy in later life.

of GARP violation using the CCEI and other standard indices that have been proposed for this purpose. Like the experimental literature, we seek to isolate DMA from standard sources of heterogeneity in choice, in our case by presenting individuals with a theoretically-grounded economic choice experiment designed to provide a stringent test of consistency with GARP.

7 Concluding remarks

New economics research emphasizes a gap between what people actually choose and what they would have chosen if they were fully attentive to their choices and had the skills and knowledge necessary to weigh costs and benefits in often complex settings. This research shows evidence that some choices are better than others and some individuals are better decision-makers than others. But it is usually difficult to evaluate the DMQ of economic choices because we do not have sufficient information to make a definitive and uncontroversial judgement. By extension, it is typically hard to identify whether, due to a lack of DMA, someone has made what appear to be choices of poor DMQ; he might have uncommon preferences, or face unobserved constraints, or have different information, or hold (reasonable) beliefs that rationalize his decisions. Standard economic analysis therefore takes a libertarian approach; in the absence of the complete data required, we assume that all choices are of good DMQ and that everyone has sufficient DMA. The libertarian approach has obvious appeal, but economists have rightly struggled to measure DMQ and to separately identify DMA from standard sources of heterogeneity in important economic outcomes. In other words, these studies are subject to identification and measurement problems.

This study suggests a new path toward solving these twin problems of identification and measurement. We offered a new large-scale experiment – employing graphical representations of standard consumer decision problems and using a diverse pool of subjects – that enables us to collect richer data than has been possible in the past. These data allow us to say that some sets of choices are of better DMQ than others, in that some choices are more rational than others. Because the data are provided by a large and heterogenous sample, we can analyze the correlates of DMQ in the laboratory and relate it to important economic outcomes like wealth. We find that differences in the experimental measures of DMQ across subjects independently explain differential patterns of wealth across households. Since wealth accumulation is determined by countless decisions, made over time in many environments, and involving a host of different tradeoffs, our findings suggest that our measure of DMQ captures aspects of DMA that apply across many sorts of economic choice problems.

Taken together, our findings provide new evidence on three important issues: (i) the validity of measuring DMQ by the consistency of choices with economic rationality, (ii) the feasibility of testing for consistency with rationality through a web-based survey on a large scale, (iii) the relative importance of heterogeneity in DMA for understanding important economic outcomes. This last issue commands special attention because DMA, unlike preferences, may be justifiably manipulated. If differences in DMA are important sources of the heterogeneity in economic outcomes, then even quite costly policy changes aimed at "soft" or "libertarian" paternalism may hold substantial promise.[29]

We conclude by underscoring three key features of the approach we have taken here. First, our measure of DMQ – the consistency of choices with GARP – dictates the experimental task: a canonical problem of selecting an allocation from a budget set. Given the task, the measure also provides the benchmark level of consistency necessary to provide a rigorous test. There are no comparable, theoretically disciplined, means of quantifying, interpreting, and evaluating laboratory or survey measures of DMA, namely tests of cognitive and non-cognitive skills. Second, informed by economic theory, the single experimental task delivers measures of both DMQ and preferences from a unified realm of decision-making. Relevant preferences cannot be recovered from performance on standard psychological tests. Third, unlike many tests of cognitive abilities or personality traits, revealed preference tests are applicable to, and comparable across, all sorts of economic choice problems. Our approach can thus be transported, with relative ease, to different decision domains. We can make domain-specific predictions and provide a unified measure of DMQ across domains. In all of these ways, the theoretical foundation of our approach drives the design of the experiment and allows diverse and disciplined use of the resulting data.

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Figure 1. Mean CCEI scores

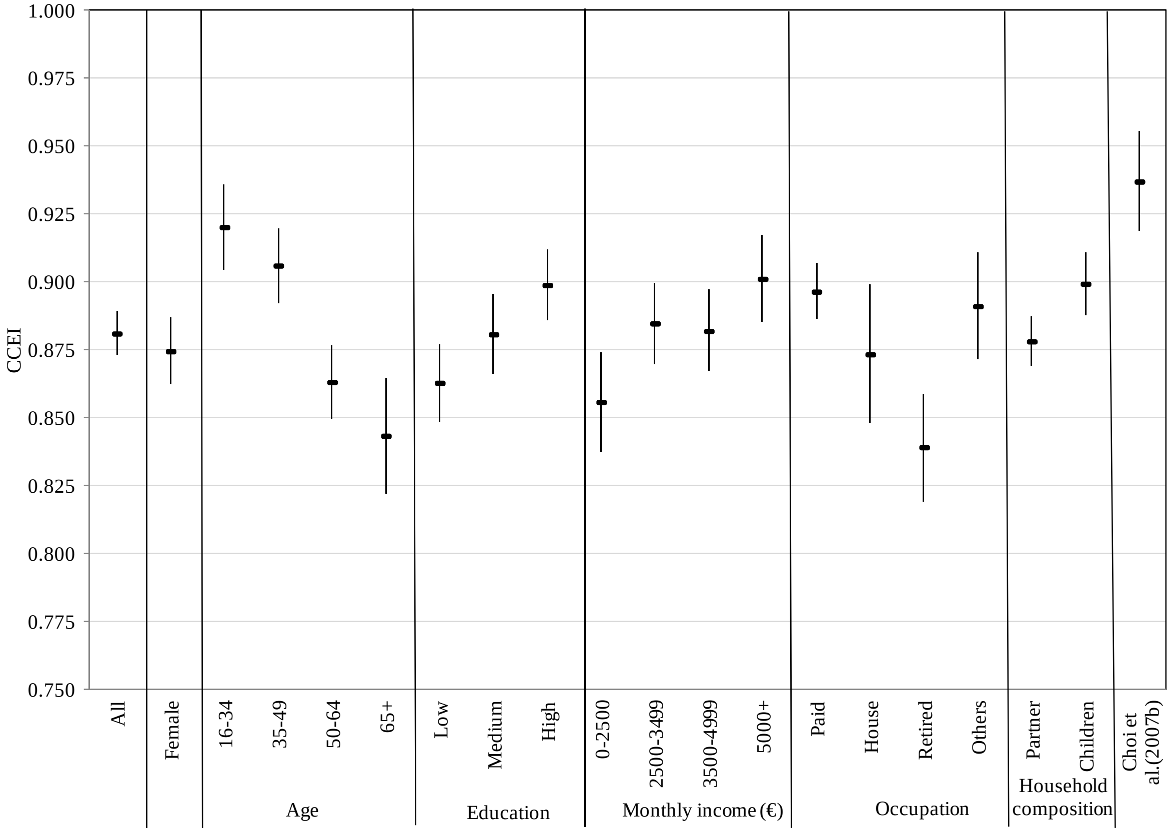

Figure 2. The average fraction of tokens allocated to the cheaper asset

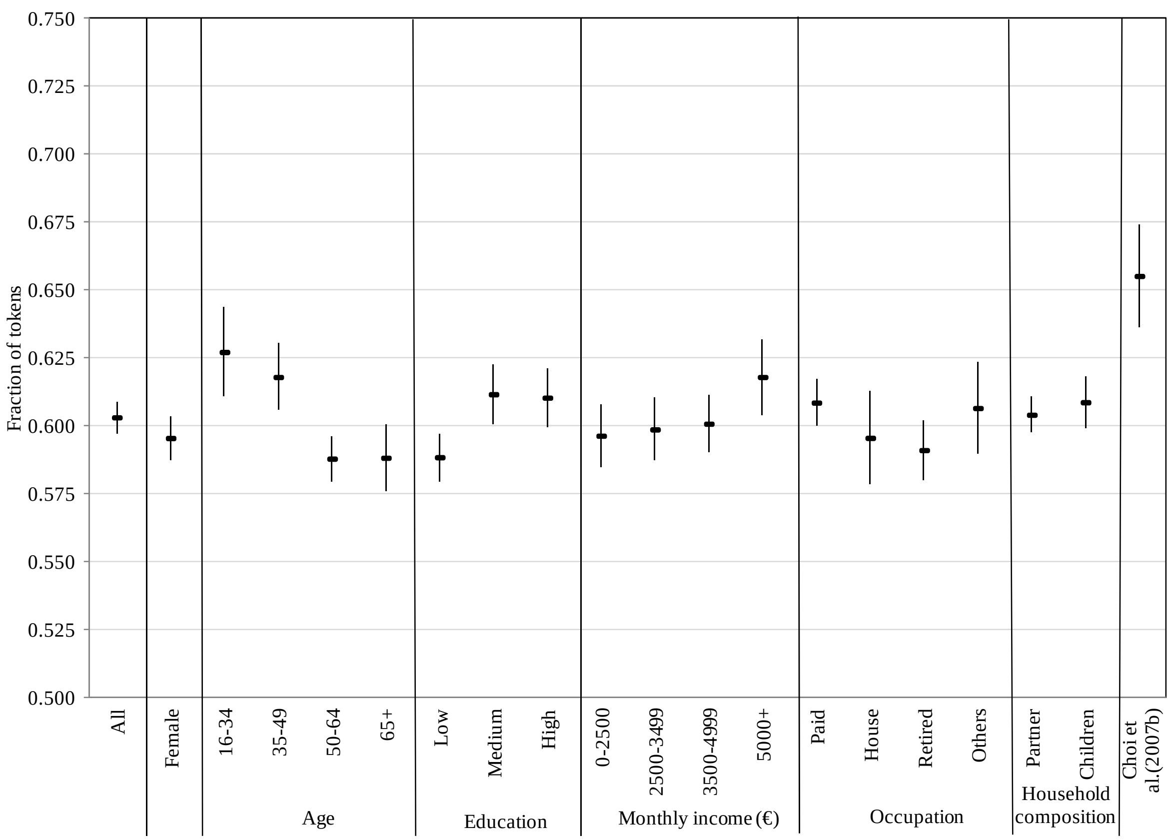

Table 1. Sociodemographic information

	Participants	Dropouts	Non-participants
Female	45.43	37.89	50.00
Age			
16-34	18.53	3.16	26.14
35-49	26.14	12.11	32.13
50-64	35.62	38.42	27.58
65+	19.71	46.32	14.15
Education			
Low	33.59	42.63	30.99
Medium	29.70	22.63	31.61
High	36.72	34.74	37.40
Household monthly income			
€0-2500	22.42	34.73	21.28
€2500-3499	25.13	26.32	18.90
€3500-4999	28.85	16.32	28.93
€5000+	23.60	22.63	30.89
Occupation			
Paid work	53.13	39.47	62.91
House work	11.59	7.89	8.78
Retired	20.90	42.63	13.95
Others	14.38	10.00	14.36
Household composition			
Partner	80.88	67.89	82.64
# of children	0.84	0.32	1.09
# of obs.	1182	190	968

Participants completed the experiment, dropouts logged in and quit the experiment, and nonparticipants were recruited for the experiment but never logged in. The low, medium and high education levels correspond to primary or pre-vocational secondary education, pre-university secondary education or senior vocational training, and vocational college or university education, respectively. We use household monthly gross income-level categories such that the proportions of participants in each category are approximately equal. The classification of levels of completed education and occupations arebased on the categorization of Statistics Netherlands (Centraal Bureau voor de Statistiek).

Table 2. The correlation between CCEI scores and subjects' individual characteristics
(OLS)

	(1)	(2)
Constant	0.887***	0.735***
	(0.022)	(0.037)
Female	-0.024***	-0.011
	(0.009)	(0.015)
Age		
35-49	-0.016	-0.007
	(0.011)	(0.020)
50-64	-0.052***	-0.077***
	(0.011)	(0.020)
65+	-0.051**	-0.081**
	(0.020)	(0.032)
Education		
Medium	0.009	0.021
	(0.011)	(0.017)
High	0.026**	0.060***
	(0.011)	(0.018)
Income		
€2500-3499	0.026**	0.026
	(0.012)	(0.019)
€3500-4999	0.020	0.006
	(0.013)	(0.020)
€5000+	0.033**	0.017
	(0.014)	(0.022)
Occupation		
Paid work	0.028	0.03
	(0.018)	(0.026)
House work	0.047**	0.039
	(0.021)	(0.030)
Others	0.037*	0.035
	(0.019)	(0.030)
Household composition		
Partner	-0.026**	-0.023
	(0.011)	(0.018)
# of children	0.001	0.001
	(0.004)	(0.007)
R^2	0.068	0.058
# of obs.	1182	1182

Omitted categories: male, age under 35, low education (primary and lower secondary education), household gross monthly income under €2500, retired, and not having a partner. Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively. Since the CCEI is a number between zero and one, we repeated the estimations reported in columns (1) and (2) using a fractional regression model (Papke and Wooldridge, 1996). The two specifications yield similar results.

Table 3. The relationship between CCEI scores and wealth

	(1)	(2)	(3)
CCEI	1.351**	1.109**	101888.0*
	(0.566)	(0.534)	(52691.9)
Log 2008 household income	0.584***	0.606***	
	(0.132)	(0.126)	
2008 household income			1.776***
			(0.4)
Female	-0.313*	-0.356**	-32484.3*
	(0.177)	(0.164)	(17523.9)
Age	-0.303	-0.008	-19148.5
	(0.347)	(0.208)	(30164.4)
Age^2	0.007	0.002	468.7
	(0.006)	(0.004)	(523.6)
Age^3	0.000	0.000	-2.9
	(0.000)	(0.000)	(2.9)
Partnered	0.652***	0.595***	46201.9***
	(0.181)	(0.171)	(17173.7)
# of children	0.090	0.109	14078.6*
	(0.093)	(0.086)	(8351.5)
Education			
Pre-vocational	0.269	0.245	14137.4
	(0.464)	(0.462)	(43449.1)
Pre-university	0.634	0.562	59035.0
	(0.478)	(0.476)	(44746.1)
Senior vocational training	0.416	0.421	28318.7
	(0.474)	(0.468)	(42419.2)
Vocational college	0.490	0.527	31341.2
	(0.451)	(0.449)	(42046.8)
University	0.725	0.685	77578.8
	(0.473)	(0.465)	(47709.4)
Occupation			
Paid work	0.206	0.226	-12657.2
	(0.322)	(0.321)	(26597.8)
House work	0.552	0.603	16876.8
	(0.406)	(0.413)	(31114.3)
Retired	0.131	0.190	16753.1
	(0.318)	(0.318)	(35165.2)
Constant	6.292	0.469	76214.4
	(6.419)	(3.598)	(559677.5)
R^2	0.179	0.217	0.188
# of obs.	517	566	568

The groupings of different levels of education are based on the categorization of Statistics Netherlands (Centraal Bureau voor de Statistiek). For a complete description see http://www.centerdata.nl/en/centerpanel. Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively.

Table 4. The robustness of the correlation between CCEI scores and wealth to the inclusion of controls for unobserved constraints

	(1)	(2)	(3)	(4)	(5)
CCEI	1.322**	1.318**	1.925***	1.888***	1.441**
	(0.570)	(0.574)	(0.672)	(0.652)	(0.578)
Log household income					
2008	19.770	1.000	0.544***	0.285*	0.616***
	(14.629)	.	(0.137)	(0.165)	(0.128)
2008^2	-2.194				
	(1.533)				
2008^3	0.082				
	(0.053)				
2006				0.232	
				(0.231)	
2004				0.215	
				(0.174)	
Female	-0.291	-0.201	-0.337*	-0.296	-0.321*
	(0.181)	(0.173)	(0.185)	(0.186)	(0.176)
Age	-0.352	-0.234	-0.285	-0.251	-0.299
	(0.350)	(0.354)	(0.373)	(0.374)	(0.347)
Age^2	0.007	0.006	0.007	0.006	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age^3	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Partnered	0.598***	0.561***	0.734***	0.707***	0.641***
	(0.181)	(0.178)	(0.192)	(0.193)	(0.179)
# of children	0.091	0.101	0.018	0.031	0.088
	(0.092)	(0.096)	(0.099)	(0.095)	(0.093)
Education					
Pre-vocational	0.313	0.339	0.266	0.165	
	(0.472)	(0.493)	(0.488)	(0.530)	
Pre-university	0.659	0.622	0.575	0.479	
	(0.486)	(0.504)	(0.505)	(0.548)	
Senior vocational training	0.430	0.448	0.467	0.383	
	(0.481)	(0.501)	(0.498)	(0.540)	
Vocational college	0.497	0.458	0.564	0.415	
	(0.461)	(0.478)	(0.471)	(0.516)	
University	0.607	0.664	0.832	0.646	
	(0.485)	(0.495)	(0.487)	(0.534)	
Occupation					
Paid work	0.226	(0.036)	0.493	0.420	0.207
	(0.324)	(0.334)	(0.355)	(0.353)	(0.324)
House work	0.553	0.395	0.734*	0.707	0.446
	(0.407)	(0.426)	(0.438)	(0.436)	(0.404)
Retired	0.147	(0.007)	0.393	0.281	0.132
	(0.320)	(0.334)	(0.361)	(0.364)	(0.321)
Constant	-47.059	0.864	5.354	3.016	6.398
	(46.275)	(6.545)	(6.93)	(7.109)	(6.484)
R^2	0.187		0.205	0.217	0.177
# of obs.	517	517	449	449	517

Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively.

Table 5. The robustness of the correlation between CCEI scores and wealth to the inclusion of controls for unobserved preferences and beliefs

	(1)	(2)	(3)	(4)	(5)
CCEI	1.379**	1.396**	1.404**	1.214*	1.237**
	(0.568)	(0.568)	(0.569)	(0.625)	(0.623)
Risk tolerance					
Quantitative (experiment)	-0.768	-0.808	-0.766		
	(0.714)	(0.711)	(0.718)		
Qualitative (survey)		0.017	0.023		
		(0.074)	(0.076)		
Qualitative (survey) missing		-0.190	-0.162		
		(0.335)	(0.482)		
Conscientiousness			0.089		
			(0.072)		
Conscientiousness missing			-0.040		
			(0.668)		
Longevity expectations					-0.034
					(0.040)
Log 2008 household income	0.589***	0.578***	0.572***	0.443***	0.434***
	(0.132)	(0.131)	(0.133)	(0.123)	(0.123)
Female	-0.316*	-0.310*	-0.323*	-0.415**	-0.417**
	(0.177)	(0.181)	(0.181)	(0.186)	(0.186)
Age	-0.308	-0.303	-0.280	-0.137	-0.158
	(0.345)	(0.345)	(0.345)	(0.904)	(0.902)
Age^2	0.007	0.007	0.006	0.005	0.005
	(0.006)	(0.006)	(0.006)	(0.018)	(0.018)
Age^3	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Partnered	0.655***	0.658***	0.642***	0.686***	0.687***
	(0.181)	(0.181)	(0.182)	(0.204)	(0.205)
# of children	0.086	0.087	0.083	0.075	0.083
	(0.093)	(0.093)	(0.093)	(0.102)	(0.102)
Education					
Pre-vocational	0.258	0.257	0.286	0.728	0.782
	(0.468)	(0.462)	(0.463)	(0.583)	(0.585)
Pre-university	0.637	0.632	0.663	0.834	0.899
	(0.481)	(0.473)	(0.470)	(0.604)	(0.616)
Senior vocational training	0.406	0.410	0.439	0.822	0.887
	(0.478)	(0.474)	(0.473)	(0.590)	(0.595)
Vocational college	0.477	0.480	0.500	0.975*	1.035*
	(0.455)	(0.449)	(0.448)	(0.571)	(0.576)
University	0.729	0.723	0.749	1.137*	1.201**
	(0.477)	(0.473)	(0.471)	(0.599)	(0.602)
Occupation					
Paid work	0.203	0.199	0.226	0.340	0.381
	(0.322)	(0.322)	(0.323)	(0.338)	(0.347)
House work	0.552	0.562	0.574	0.631	0.672
	(0.407)	(0.408)	(0.415)	(0.459)	(0.463)
Retired	0.140	0.136	0.161	0.578	0.622
	(0.320)	(0.320)	(0.321)	(0.406)	(0.417)
Constant	6.840	6.883	6.496	3.777	4.411
	(6.361)	(6.357)	(6.395)	(15.258)	(15.256)
R^2	0.179	0.176	0.176	0.163	0.163
# of obs.	517	517	517	414	414

Risk aversion in the experiment measured by the average fraction of tokens allocated to the cheaper asset. Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively.

Table 6. Evaluating alternative measures of decision-making quality

	(1)	(2)	(3)	(4)
CCEI	1.253*	1.401*	1.269*	1.177**
	(0.712)	(0.729)	(0.729)	(0.583)
CCEI (combined dataset)	0.099			
	-0.38			
von Gaudecker et al. (2011)			0.927*	
			(0.485)	
Cognitive Reflection Test (CRT)				0.120*
				(0.071)
CRT missing				-0.203
				(0.237)
Log 2008 household income	0.586***	0.388*	0.383*	0.577***
	(0.132)	(0.155)	(0.154)	(0.132)
Female	-0.314*	-0.218	-0.207	-0.292*
	(0.177)	(0.212)	(0.211)	(0.176)
Age	-0.301	-0.437	-0.361	-0.323
	(0.346)	(0.363)	(0.363)	(0.349)
Age^2	0.007	0.009	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
Age^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Partnered	0.653***	0.907***	0.926***	0.690***
	(0.181)	(0.230)	(0.228)	(0.181)
# of children	0.089	0.105	0.096	0.091
	(0.093)	(0.114)	(0.113)	(0.092)
Education				
Pre-vocational	0.266	0.183	0.093	0.213
	(0.5)	(0.504)	(0.468)	(0.464)
Pre-university	0.629	0.56	0.375	0.569
	(0.5)	(0.524)	(0.487)	(0.474)
Senior vocational training	0.412	0.316	0.153	0.345
	(0.5)	(0.527)	(0.490)	(0.473)
Vocational college	0.484	0.727	0.611	0.396
	(0.5)	(0.482)	(0.448)	(0.450)
University	0.716	0.779	0.592	0.590
	(0.5)	(0.500)	(0.463)	(0.476)
Occupation				
Paid work	0.210	0.819	0.725	0.184
	(0.324)	(0.489)	(0.486)	(0.319)
House work	0.555	0.770	0.754	0.530
	(0.406)	(0.565)	(0.561)	(0.403)
Retired	0.135	0.507	0.461	0.084
	(0.319)	(0.478)	(0.469)	(0.312)
Constant	6.237	10.056	8.355	6.855
	(6.424)	(6.976)	(6.990)	(6.464)
R^2	0.177	0.225	0.232	0.181
# of obs.	517	326	326	517

The CCEI scores for the combined dataset is computed after combining the actual data from the experiment and the mirror-image data. Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively.

Table 7. The sources of the relationship between households' net worth and CCEI scores

	(1) Have checking	(2) Fraction in checking	(3) Have saving	(4) Fraction in saving
CCEI	0.03	-0.098*	-0.047	-0.162*
	(0.032)	(0.057)	(0.053)	(0.097)
Log 2008 household income	0.001	-0.029**	0.003	-0.068***
	(0.002)	(0.013)	(0.010)	(0.021)
Female	0.007	0.023	0.014	0.038
	(0.005)	(0.020)	(0.019)	(0.033)
Age	-0.003	0.025	-0.007	-0.002
	(0.009)	(0.048)	(0.046)	(0.067)
Age²	0.000	-0.001	0.000	0.000
	0.000	(0.001)	(0.001)	(0.001)
Age³	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Partnered	-0.005	-0.031	0.017	-0.054
	(0.004)	(0.020)	(0.022)	(0.033)
# of children	0.000	-0.004	-0.025*	-0.043***
	(0.001)	(0.010)	(0.014)	(0.013)
Education				
Pre-vocational	-0.007	0.002	0.038	0.010
	(0.007)	(0.063)	(0.068)	(0.084)
Pre-university	-0.017	-0.022	-0.005	-0.074
	(0.018)	(0.063)	(0.075)	(0.087)
Senior vocational training	0.005	0.000	0.044	-0.041
	(0.004)	(0.063)	(0.069)	(0.085)
Vocational college	0.002	-0.007	0.013	-0.042
	(0.003)	(0.061)	(0.069)	(0.083)
University	0.003	0.008	0.018	-0.077
	(0.003)	(0.064)	(0.073)	(0.086)
Occupation				
Paid work	(0.005)	(0.012)	0.014	0.063
	(0.004)	(0.034)	(0.037)	(0.051)
House work	(0.002)	(0.030)	(0.012)	(0.028)
	(0.002)	(0.047)	(0.051)	(0.065)
Retired	(0.000)	(0.017)	0.015	0.065
	(0.002)	(0.033)	(0.039)	(0.056)
Constant	0.998***	0.106	1.126	1.448
	(0.172)	(0.822)	(0.848)	(1.288)
R^2	-0.007	0.021	-0.011	0.083
# of obs.	512	512	502	502

Table 7.
(Continued)

	(5) Have stocks	(6) Fraction in stocks	(7) Have a house	(8) Fraction in house
CCEI	0.167	0.001	0.352**	0.324**
	(0.163)	(0.050)	(0.152)	(0.129)
Log 2008 household income	0.148***	0.013	0.134***	0.096***
	(0.031)	(0.009)	(0.029)	(0.024)
Female	0.007	0.009	-0.038	-0.066
	(0.050)	(0.013)	(0.050)	(0.043)
Age	0.078	0.013	-0.025	-0.009
	(0.098)	(0.022)	(0.090)	(0.073)
Age²	-0.001	0.000	0.001	0.000
	(0.002)	0.000	(0.002)	(0.001)
Age³	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Partnered	0.005	-0.007	0.207***	0.127***
	(0.049)	(0.014)	(0.051)	(0.044)
# of children	0.003	0.000	0.048**	0.063***
	(0.026)	(0.007)	(0.020)	(0.019)
Education				
Pre-vocational	-0.069	-0.042	0.029	0.068
	(0.127)	(0.049)	(0.123)	(0.110)
Pre-university	0.036	-0.012	0.096	0.079
	(0.137)	(0.053)	(0.128)	(0.115)
Senior vocational training	-0.045	-0.030	0.067	0.068
	(0.131)	(0.048)	(0.124)	(0.112)
Vocational college	0.022	-0.024	0.085	0.058
	(0.127)	(0.049)	(0.121)	(0.108)
University	0.195	0.009	0.094	0.067
	(0.135)	(0.051)	(0.126)	(0.113)
Occupation				
Paid work	0.071	(0.025)	0.043	0.018
	(0.080)	(0.031)	(0.076)	(0.069)
House work	0.012	(0.040)	0.088	0.146
	(0.101)	(0.029)	(0.102)	(0.089)
Retired	0.054	(0.020)	(0.013)	0.044
	(0.090)	(0.029)	(0.081)	(0.071)
Constant	-3.152*	-0.317	-1.047	-1.151
	(1.856)	(0.398)	(1.760)	(1.419)
R^2	0.079	0.002	0.148	0.123
# of obs.	514	514	479	479

Standard errors in parentheses. *, **, and *** indicate 10, 5, and 1 percent significance levels, respectively.