Internet Access and Cognitive Ability: An Analysis of the Selectivity of Internet Interviews in the Cognitive Economics Survey

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1 Introduction

Differences in findings drawn from data collected by internet and mail surveys represent a mixture of mode effects generated by different responses to the same question in the two modes and selective differences in coverage of the population that respond to the two modes. In this chapter, we use detailed information on the cognitive abilities of respondents in the Cognitive Economics Survey (CogEcon) to study the implications of selection on cognitive ability for studies of an older population who participates in internet surveys. From earlier studies of internet interviewing of the Health and Retirement Survey (HRS) sample, we know that internet access is strongly related to age and education in the older population (**?**). If

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valid inferences about population characteristics and behavior are to be drawn from web surveys, it is important to understand this selectivity, make appropriate statistical adjustments or, if that is not feasible, consider supplemental data collection to overcome selectivity biases associated with internet interviewing.[1] These issues are of particular importance for studying economic decision-making by older populations because decisions made by older people about finances, retirement and health are significantly influenced by their cognitive abilities which, in turn, are correlated with age and education.

The Cognitive Economics Survey (CogEcon) is an innovative new survey administered by mail and internet to a national sample of 1222 persons, age 51 and older and their spouses regardless of age, who are participants in the Cognition and Aging in the USA study (CogUSA)[2]. A major goal of the CogUSA study is to provide scientific guidance to the HRS in order to improve its measures of higher order cognitive abilities which are theorized to play an important role in determining the quality of economic and health decisions by older Americans. As discussed in **?**, one of the most widely accepted theories of cognitive abilities is the *Gf-Gc* theory (**????**). Primary abilities are divided into two broad dimensions: fluid intelligence (Gf), broadly defined to include reasoning abilities, and crystallized intelligence (Gc), accumulated knowledge and skill. The distinction between fluid and crystallized intelligence is similar to the notion of ability versus human capital in labor economics. CogUSA measures many components of fluid and crystallized intelligence during an extremely detailed, three-hour cognitive assessment of sample members.

The CogEcon survey, supported by a separate NIA program project led by Robert Willis, was designed by a team of economists to help understand the cognitive bases of economic decision-making.[3] The CogEcon questionnaire, which has a median length of 53 minutes on

[1]See **?**, for a discussion of these issues in the context of HRS.

[2]The CogUSA Study is sponsored by the National Institute of Aging, grant number R37 AG007137, "Assessing and Improving Cognitive Measurements in the HRS," led by John J. McArdle, PI, a quantitative psychologist at the University of Southern California, who is a co-investigator in the Health and Retirement Study.

[3]The Cognitive Economics Survey is supported by NIA program project P01 AG026571, "Behavior on Surveys and in the Economy Using HRS," Robert J. Willis, PI. In addition to Willis, the design team

the internet version, includes a battery of twenty-five questions on financial sophistication, detailed measures of income, wealth and portfolio allocation plus measures of risk tolerance, self-assessed financial knowledge, use of records and other sources of information and several questions on decision-making. By linking psychological and economic measures, the combined survey provides crucial evidence about which of the new cognitive measures in CogUSA would be most productive to add to the HRS.

2 Survey design

2.1 The CogUSA Study

The CogUSA Study consists of three survey components, as depicted in Figure 1. The study begins with a 40 minute telephone interview that replicates the sections of the HRS questionnaire on demography, health and cognition.[4] These wave 1 interviews were conducted between June and December 2007. For each respondent this telephone survey was followed as quickly as possible—ideally, within a week—by wave 2, a three hour face-to-face assessment of the cognitive abilities of respondents on a large number of different tasks measuring components of fluid and crystallized intelligence. Finally, the wave 3 telephone interview wave took place at a randomized interval of one to twenty-four months following the personal interview. In addition to re-testing several components of ability using a telephone administration, this second telephone interview administered the same subjective probability questions fielded by HRS during its 2008 wave.

One of the goals of the CogUSA is to develop efficient methods of assessing well-recognized components of intelligence and personality that can be administered by surveys using either face-to-face or telephone administration.[5] For example, McArdle, Rodgers, Fisher, Horn, and

includes Daniel Benjamin, Miles Kimball, Claudia Sahm, Matthew Shapiro, and Tyler Shumway. Gwen Fisher, Brooke Helppie McFall, and Joanne W. Hsu oversaw the internet and mail data collection and also provided valuable help on the survey design.

[4]See http://hrsonline.isr.umich.edu for more information about the HRS.

[5]See Appendix A for a full description of these measures.

Woodcock developed an adaptive Number Series test that was piloted in HRS experimental modules in 2004 and 2006.[6] The adaptive Number Series test covers the same range of ability covered by 47 items in the standard Woodcock-Johnson (WJ-III) test in about four minutes and no more than six questions. This adaptive test is repeated in the CogUSA telephone interview, while the full WJ-III number series test is conducted in the in-person wave.[7]

Among the many cognition measures in our survey, we focus our attention to standardized scores of three tests: Number Series, Retrieval Fluency and Vocabulary, all drawn from the in-person interview (wave 2). In preliminary research with the CogEcon data, the Number Series test, which is a measure of quantitative reasoning, has been shown to be more significantly related to measures of economic knowledge and economic status than other cognitive measures. Vocabulary, a test from the Wechsler Adult Intelligence Scale (WAIS), measures a form of crystallized intelligence that includes expressive vocabulary, verbal knowledge, and fund of information. Lastly, Retrieval Fluency is a measure of long-term retrieval from stored knowledge, also from the WJ-III. In this test, respondents are asked to name as many items as possible in a specific category during a short period of time. These three were chosen to cover disparate forms of cognition.

2.2 The Cognitive Economics Survey

Members of the CogUSA sample whose cognitive ability was assessed in wave 2 face-to-face interviews were invited to participate in the CogEcon mail/internet survey in 2008. In addition, CogEcon fielded a 2009 Post-Crash survey to follow up with respondents after the economic crisis, and plans are underway for new waves of data to be collected in the fall of 2011 and in 2013. The CogEcon Study content includes many aspects of economic decision-making, including income, assets, and another form of crystallized intelligence, financial

[6]The number series test asks a person to fill in the missing number in a sequence. An easy example is 1, 2, 3, _ ; a little harder one is 2, 4, _ , 256. (Note that the actual items are copyrighted and cannot be reproduced). An adaptive test can dramatically reduce the number of items needed to assess a person's ability by asking questions that are of most relevance to a person's ability.

[7]The 47-item test is "somewhat adaptive," so that few respondents answer all 47 items.

sophistication/literacy (see http://cogecon.isr.umich.edu/ for more details).

The CogEcon sample frame consists of the 1222 individuals, including age-ineligible spouses, who completed the first two waves of CogUSA. The invitees range in age from 38 to 96 years, with a mean age of 64.0 years. Of the invitees, 816—just over two-thirds of respondents[8]—reported using the internet regularly.

To avoid conflict with wave 2 of the CogUSA survey, the CogEcon survey was divided into two releases; 921 were assigned to the first release (fielded in February and March of 2008), and 301 were assigned to the second (fielded in July 2008; see Figures 1 and 2). All individuals in the first release who indicated that they had used the internet "regularly"[9] during the baseline wave 1 telephone interview of the CogUSA were sent a letter inviting them to participate in an internet interview; those without access were sent a letter with a mail version of the survey enclosed.

In the first CogEcon sample release, 624 respondents were invited to completed the internet version of the survey and 297 to complete the mail version. In the second sample release, we invited all 301 persons to complete a mail survey regardless of internet access—no internet survey was administered in this second release. Of these, 189 had reported at baseline that they used the internet regularly. Since individuals were randomly assigned to sample releases, assigning these individuals to a mail survey forms the basis for a randomized mode experiment, analyzed in detail in **?**.

Our analysis in this chapter takes two primary forms, shown in Figure 3. First, we characterize differences, if any, between those reporting internet access and those without access on the basis of attributes measured in CogUSA. This is represented as the dotted

[8]This is substantially higher than the internet usage rate found in the HRS. This is possibly due to the sampling frame used for the CogUSA, based on random-digit dialing. Furthermore, since CogUSA was described as a study on cognition and aging in the recruitment letter from the Survey Research Center, those with lower cognition may have declined to participate in higher numbers than those in the HRS sample. Since internet access is related to ability, such an effect would lead to fewer respondents without internet access in the CogUSA sample.

[9]Question number W303 from HRS was used. It reads: "Do you regularly use the World Wide Web, or the Internet, for sending and receiving e-mail or for any other purpose, such as making purchases, searching for information, or making travel reservations?"

rectangle in the first row of the figure (maximum sample size: 1222). Because CogUSA was implemented in the same mode at each wave for all respondents—telephone for wave 1 and in-person for wave 2—this analysis will not be subject to mode effects. Second, we restrict the analysis to the CogEcon sub-sample. Since Release 1 of CogEcon was mixed-mode, some differences may be due to mode effects rather than selectivity. Comparing internet users and non-users in the mail-only Release 2 provides an opportunity to isolate selection issues. This comparison is shown in the second row of Figure 3.

3 Results

3.1 Internet Coverage and Determinants of Access

While respondents with internet access outnumber those without at a rate of nearly two to one, the probability of internet access differs dramatically by the age and education of CogUSA respondents. This can be seen in the probit regression results in the first column of Table 1 and is very similar to the pattern of internet access seen in HRS data. The second column adds the respondent's standardized Number Series score (a measure of fluid intelligence), Vocabulary score (a measure of crystallized intelligence), and Retrieval Fluency (a measure of long-term retrieval), all obtained in the CogUSA in-person survey. Both Number Series and Vocabulary have a strong positive relationship to internet access. A one standard deviation increase in the Number Series score is associated with an 8 percentage point increase in the probability of internet access. Likewise, a one standard deviation increase in Vocabulary increases internet access by 0.06. This implies that respondents with internet access tend to be of considerably higher ability than those without, even after controlling for age and education. Retrieval Fluency is also positively related to internet access, but the coefficient is not precisely estimated. The third column adds coupleness status, coded as one if the respondent is married or partnered and zero otherwise. The slight increase in the likelihood for internet access for those in couples is unsurprising given

economies of scale and the ease of sharing computers and internet access within a household.

A scatter plot of predicted probabilities from the regression in column (2) is presented in Figure 4 along with non-parametric lowess estimates of the unconditional probability of access by age. The lowess plot shows that on average, 60-year-old respondents in CogUSA have an 80% predicted probability of internet access, while for the oldest members this probability is 20% or below. The scatter of points around the lowess plot indicates considerable variation in the probability of being in the internet sample that is associated with differences in education and cognition.

Ability differentials between the internet and mail eligible samples are shown more directly in Figure 5, which presents kernel density estimates of the distribution of the standardized cognition scores in the two samples. The mean Number Series scores in the internet and mail samples are, respectively, 0.29 and -0.60, with standard deviations of 0.85 and 1.003. Thus, overall there is about a 0.89 difference in means (nearly one standard deviation) in the Number Series scores between the two subsamples. Internet users have Vocabulary scores that exceed those of non-users by 0.76 on average, and their distributions are particularly different from each other. Internet users also have higher Retrieval Fluency scores, though the dispersion of Retrieval Fluency is much smaller than Number Series and Vocabulary.

We can also consider variables from the CogEcon study; doing so, however, restricts the sample to at most 985 observations. Furthermore, these variables may be subject to mode effects. Running the three specifications in Table 1 on the smaller CogEcon sample yields point estimates that are very similar to those found in the CogUSA sample (CogEcon results reported in Table 2), so we can be confident that the CogEcon sample is representative of the larger CogUSA sample.

In Table 3, we consider economic determinants of internet access, and therefore restrict the analyses to those who completed the CogEcon study. Column (1) reports results with only demographic explanatory variables. Column (2) also includes the three cognition scores as well as the standardized financial sophistication score, a measure of crystallized intelli-

gence obtained in the CogEcon study. Including financial sophistication somewhat weakens the effect of the Number Series score relative to column (2) in Table 2. The positive and statistically significant effects of Number Series, Retreival Fluency, and financial sophistication score all remain. This provides additional evidence that those who participate in the internet sample are of higher ability than their counterparts in the mail sample.

Lastly, we investigate the relationship of internet access to income and wealth. We use the natural log of earnings (with those not working coded as zero) and the natural log of total wealth (with negative and zero values of wealth coded as zero). Column (3) of Table 3 reports regressions including demographics, log income, and log wealth, excluding cognition, while the last column includes all covariates.

Greater earnings and wealth both increase the probability of having internet access. The effect of earnings suggests that occupational exposure to computing technology may have a role in internet access for older Americans. This may also reflect some of the effects of being retired and having less of a need for computers or internet access for work.[10]

However, including cognition and financial literacy weakens the effects of earnings and wealth. Comparing columns (3) and (4) of Table 3, the marginal effect of log wealth is reduced by about 40 percent, from 0.013 to 0.008, with the inclusion of the two scores. Furthermore, the inclusion of cognition and financial sophistication reduces the effect of education from 0.038 to 0.012, or almost 70 percent.

The effect of cognition is not quite as sensitive to the inclusion of economic variables (see columns (2) and (4)). This suggests that even after controlling for standard demographic and economic variables, there is still selection into internet access on the basis of cognitive ability. A one-standard deviation increase in the Number Series score increases the probability of internet access by 0.05, and the same increase in Vocabulary is associated with a 0.08 increase in internet access. In the full specification in the last column, demographic and cognition (Number Series and Vocabulary) variables are statistically significantly related to internet

[10] We unfortunately do not have information on whether respondents access the internet from home, work, or elsewhere.

access; economic variables are positive but not statistically significant here.

These results used pooled data from respondents without internet access, who necessarily responded by mail, and those with internet access, who were randomly invited to respond by mail or internet. Of the variables in Table 3, earnings, wealth and financial literacy were collected in CogEcon using the two modes; the demographic variables were collected in CogUSA using the same mode for all respondents. To verify that our results are not driven by mode effects, we repeat the analysis of Table 3 using only CogEcon Release 2: 146 with internet access, and 83 without. All of these individuals completed mail surveys, so group differences are not due to mode. The results of these regressions, reported in Table 4, are largely consistent with the results from the complete sample. The main exception is that in the full sample, the effect of log wealth exceeded that of log earnings, and the opposite is true here in the mail-only Release 2 subsample. Because in both specifications the marginal effect of earnings is not statistically different from that of wealth (p-values of 0.6130 and 0.4719 in the full sample and the Release 2 subsample, respectively), this discrepancy is not problematic.

3.2 Response rates in CogEcon

Response rates to the CogEcon survey differed quite dramatically by mode. CogEcon achieved an overall response rate of 86.72% for internet invitees and 71.62% for mail invitees in Release 1.[11] Of those who were initially assigned to the internet mode, 83.4 percent submitted a completed questionnaire either by internet or mail while 74.7 percent of those initially assigned to the mail mode returned a questionnaire. A probit model of response rates to Release 1 shows that being an internet user who was invited to take the internet

[11] Of the 624 who were invited to do the internet survey in CogEcon Release 1, 492 (79.2 percent) submitted complete interviews. There were also 25 "partial" interviews by people who failed to hit the "submit" button at the end of the interview; some of these are largely complete, while others have very few questions answered. In addition, 251 mail interviews were submitted, including 30 respondents with internet access who eventually requested paper questionnaires. In sum, 921 CogUSA respondents were invited to participate in Release 1 of the CogEcon Survey and 743, or 80.6 percent, returned completed questionnaires.

survey is associated with a 0.12 increase in the probability of response (the first column of Table 5).[12] We also see that the Number Series score also has a positive, statistically significant impact on the probability of response.

To see if this difference is more a function of unmeasured ability or personality differences between mail and internet invitees than a true mode effect, we analyze Release 2 data, in which respondents with and without internet access were all invited to complete a mail survey. As can be seen in the second column of Table 5, having internet access is *not* associated with increased likelihood of response. Likewise, we no longer see an impact of Number Series on response.[13] Therefore, the results of the Release 1 response rate analysis are likely due to mode effects (see **?**).

Personality We also investigated difference in personality by internet access. The Big Five personality traits—extroversion, agreeableness, conscientiousness, neuroticism, and openness—do not vary systematically between web users and non-users (see Section A for more details on personality traits). Likewise, Need for Cognition also does not vary. None of these personality traits are statistically significant in univariate regressions of internet access, nor are they significant when added to the full specifications of determinants of access with demographics, cognition, and wealth. In addition, the Big Five traits and Need for Cognition also do not predict response to the 2008 CogEcon study. These results are not reported here for brevity.

[12] These probit regressions exclude 30 internet invitees who eventually responded using a mail questionnaire included in a reminder letter.

[13] Similar results hold when analyzing all mail surveys in both releases.

4 Discussion

4.1 How does selectivity of the internet sample affect inferences from data?

One of the major goals of the CogEcon/CogUSA collaboration is to provide evidence on the relationship between cognitive ability and economic decision-making. The cognitive measures obtained in CogUSA may be interpreted within the theory of "fluid and crystallized intelligence" (**??**). Crystallized knowledge (Gc) is thought to represent acculturated knowledge, and fluid reasoning (Gf) is thought to represent reasoning and thinking in novel situations.[14] Connections between *Gf/Gc* theory and human capital theory have been developed by **?** and have been used to study the accumulation of financial knowledge and financial decision-making by **?**.

In this section, we examine the age trajectories of the Number Series score, a well-established component of fluid intelligence collected in the CogUSA, and two measures of different types of crystallized intelligence: Vocabulary, a well-established measure from CogUSA, and a newly developed measure of financial sophistication from the CogEcon survey. From an economic point of view, the financial sophistication score measures a form of human capital which, from a psychological point of view, is largely a component of crystallized intelligence.[15] Our interest in this chapter is simply to illustrate the degree to which the selectivity of an internet sample might produce misleading inferences utilizing data from the full CogUSA sample and both the internet and mail components of the CogEcon survey.

Over the lifespan, fluid reasoning ability increases rapidly during childhood and adolescence, reaching a peak between ages 15-20, and then begins a linear decline that continues

[14]The current form of $GfGc$ theory (**?**, Horn, 2003) contains 8 broad cognitive functions: 1. Fluid Reasoning (Gf). 2. Acculturation Knowledge (Gc). 3. Short-term memory (Gsm) 4. Processing Speed (Gs) 5. Long-term Retrieval (Glr), 6. Visual Processing (Gv), 7. Auditory Processing (Ga). 8. Quantitative Knowledge (Gq). For purposes of our model, we consider only the first two functions.

[15]Psychometric analysis of the financial sophistication measures is currently underway by several researchers in the Willis P01 project (NIA program project P01 AG026571).

among cognitively normal adults without dementia until death. In contrast, crystallized abilities tend to continue increasing at least through middle age and then remain relatively unchanged through the rest of life. In other words, patterns of age-related decline are evident for fluid intelligence, but not crystallized intelligence. These theoretically predicted patterns are illustrated in Figure 6. Using the full CogUSA sample, non-parametric lowess estimates of the age trajectories of the Number Series, Vocabulary, and financial sophistication scores are presented in Figure 7.

As predicted by *Gc/Gf* theory, the Number Series score decreases linearly throughout the 50+ age range of the sample while the financial sophistication measure only begins declining at late ages. From a substantive point of view, it is important to note that these cross-sectional age trajectories represent an unknown mix of age and cohort effects.[16] Given the methodological focus of this chapter on selectivity issues, this distinction is not critical. For our purposes, the key message of Figure 7 is that the trajectories we see in the full sample are broadly consistent with theoretical expectations.

The fact that internet access is strongly correlated with age, education, Number Series score, and Vocabulary score implies that participation in an internet survey will be selective on fluid and crystallized intelligence, and both quantitative and verbal skills. The pattern of selection by age is illustrated in the first panel of Figure 8, in which non-parametric lowess curves of the standardized Number Series score versus age are plotted separately for respondents with internet access, respondents without internet access, and the full sample; the second and third panels display the same for Vocabulary and financial sophistication scores. While the rate of decline is similar for mail and internet eligible respondents, the slope of the full sample age profile is much steeper, reflecting differential selection at older ages. Since the full sample age profile is a weighted average of the age profiles for the mail

[16]There is good reason to think that cohort effects are important for these measures. The "Flynn Effect" refers to a well-documented increase across cohorts of scores on tests of fluid intelligence. (See **?** and **?** for an extensive discussion of these findings.) Examination of gender differences in the financial literacy scores shows a decline in scores for females at older ages which is almost surely a cohort effect reflecting a traditional household division of labor. **?** addresses possible cohort effects by looking at intra-couple differences in financial sophistication.

eligible group and the internet eligible group, these slopes are consistent with the declining predicted probability of having internet access with age as shown in Figure 4.

At younger ages, the full sample is dominated by internet eligible respondents; those who are mail eligible are of lowest ability. Likewise, at older ages, our full sample is composed primarily of mail respondents, and those captured in the internet eligible are of very high ability. Therefore, not only does the internet eligible sample select on the basis of age, it also selects on the basis of ability at both ends of the age distribution. An internet-only sample would miss an increasing number of persons, particularly those with lower ability, at older ages. Because of selection, it is clear that an internet-only sample would lead to an overestimate of level of intelligence and an underestimate of the rate of cognitive decline with aging.

Analysis of survey data must take selectivity into account. In the case of the CogEcon survey, we recognized that selection would be an issue when we began thinking of administering an internet survey and, therefore, decided to supplement it with a mail survey in order to cover the entire CogUSA sample. However, this is not an option with many internet surveys.

4.2 Propensity score weighting

In the above analysis, we have established that internet users differ fundamentally from internet non-users, and that a internet-only sample would be subject to selection on cognition in addition to standard demographic variables. Propensity score weighting is one method of correcting for the selection bias arising from variation in internet access. In this section, we create weights based on our probit regressions of internet access and compare weighted means from a internet-only subsample to means from the a full sample of internet users and non-users. For simplicity, we treat the full CogUSA sample as representative random sample of the population of interest in order to abstract away from non-response issues within the CogUSA study and attempt to weight the internet sub-sample to resemble the full sample.

? developed the use of propensity scores to adjust for non-random assignment of treatments in observational studies (see also **?**). The valid use of propensity scores requires *strong ignorability*. Following the notation in **?**, strong ignorability requires that for an outcome of interest Y, and X covariates used to estimate the propensity for internet access I,

$$P(I = 1|X, Y) = P(I = 1|X) \text{ for almost all X and Y.} \tag{1}$$

In our context, this requires that the outcome of interest Y and internet use I are independent, conditional on a set of covariates X.

If the strong ignorability condition is met, inverse probability weights can be used to construct consistent estimates of parameters of the distribution of Y (**?**). We use predicted probabilities estimated from the two probit regressions from Table 1; the weights are the inverse of these predicted probabilities, normalized so the weights have a mean of one. We construct one set of weights using only standard demographic information as explanatory variables: age, sex, education, and coupleness status. The second set of weights also includes cognition variables, which unlike the demographic variables are not standard data collected by surveys. Figure 4 displays a scatterplot of these propensity scores.

This comparison of the two sets of weights is similar to work on whether attitudinal or lifestyle questions are useful additions to propensity score estimates for weighting data. Harris Interactive, a company that specializes in web surveys, uses a set of attitudinal variables called "webographic" variables. **?** find that propensity scores using "webographic" variables improve some of the bias that emerges from a web-only sample. Indeed, weighting using propensity scores from demographic variables alone produce large discrepancies in "webographic" measures for web-using and non-using samples (**?**). Here, we continue our focus on the role of cognition.

To analyze the weighted and unweighted descriptive statistics of web-users and the full sample, we consider the prevalence of 14 health conditions: diabetes, high blood pressure,

cancer, lung disease, heart conditions, stroke, arthritis, past and present smoking status, and others. Each variable is coded as one if the respondent reported the condition, and zero otherwise; these were asked on CogUSA and therefore are not subject to mode effects. We also considered a number economic variables: currently working for pay (collected by telephone for all respondents in the third wave of CogUSA), an indicator for owning one's own home, and values of retirement wealth and total wealth. Internet users and internet non-users have statistically significant differences in means for 11 of the 14 health conditions and all of the economic variables. The two groups do not have statistically significant differences in means for having fallen in the last two years, ever smoked, psychological or emotional problems, and incontinence.

Table 6 reports means of each variable, with the the mean of the CogUSA "population" in column (1) and means from the internet-using subsample with and without weights in columns (2) through (4). For nearly all outcomes with statistically significant differences between internet users and non-users, applying weights (whether the weights in column (3) or column (4)) reduces the difference means of the internet sample with the full sample. The only exception is lung disease: the weights without cognition increase the difference, but the weights with cognition do bring the weighted internet-only mean closer to the full sample mean.

For 11 of the 14 health variables, using weights computed with cognition scores reduced the gap between internet-only and full sample means more than weights computed using only demographic characteristics. In particular, weights without cognition exacerbated differences in means for three of the four outcomes for which web-only means were similar to the full sample mean (fallen in the last two years, ever smoked, and incontinence), while weights with cognition preserved the similarities between web users and the full sample. However, for three of the four economic variables, the weights without cognition closed the gap more than the weights with cognition. In our case, it appears that propensity score weights based on our analysis do help correct for selectivity in some, but not all, outcomes.

5 Conclusion

In general, data collected through internet and mail surveys can yield differences in data that are a combination of differential responses to the same question in the two formats and selection effects due to differing coverage of the population responding to each mode. By using data obtained in the face-to-face interview of CogUSA in conjunction with data from the mixed-mode CogEcon survey, we have been able to analyze the selectivity of internet interviews without being subject to mode effects.

After controlling for age, sex, and education, we find that the Number Series and Vocabulary scores have a strong positive relationship to internet access. The effect of the Number Series score is only reduced with the inclusion of the financial sophistication score, a measure of crystallized intelligence.

Our results suggest that those with internet access will tend to be of higher ability, both in terms of fluid and crystallized intelligence, than those without internet access. In addition, the degree of selectivity increases as respondents' ages increase. First, the older the person, the less the likely he or she is to be included in our internet sample. Since fluid intelligence declines with age, that means an internet sample loses more and more people—particularly those with low fluid intelligence and those who have acquired little financial knowledge—as the age of respondents increases. Consequently, not only would an internet-only sample overestimate the abilities and knowledge of participants, it would underestimate the rates of decline with age in fluid and crystallized intelligence relative to data with full population coverage.

6 Figures and Tables

Figure 1: Timing of the Cognitive Economics Study

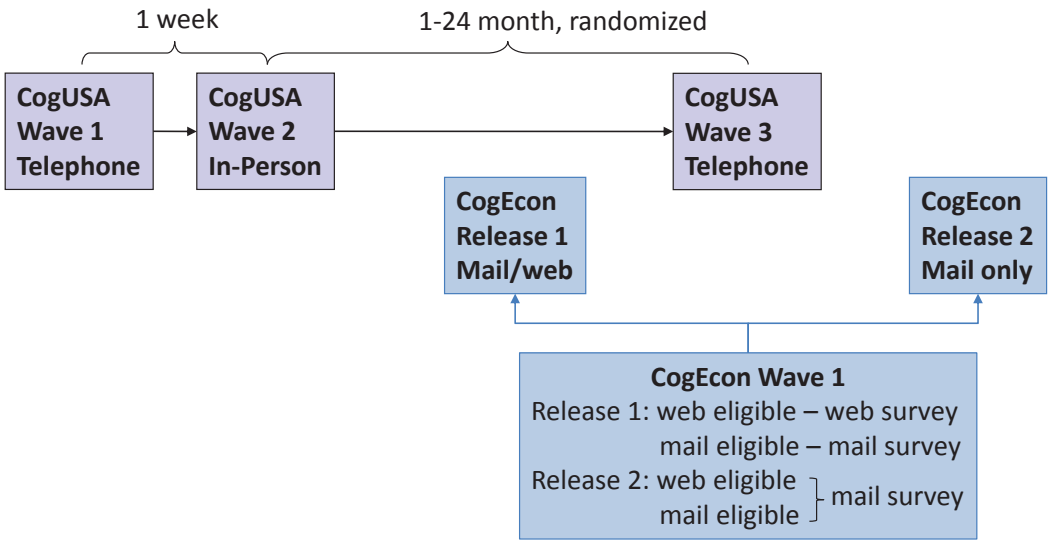


Figure 2: CogUSA and CogEcon flow chart

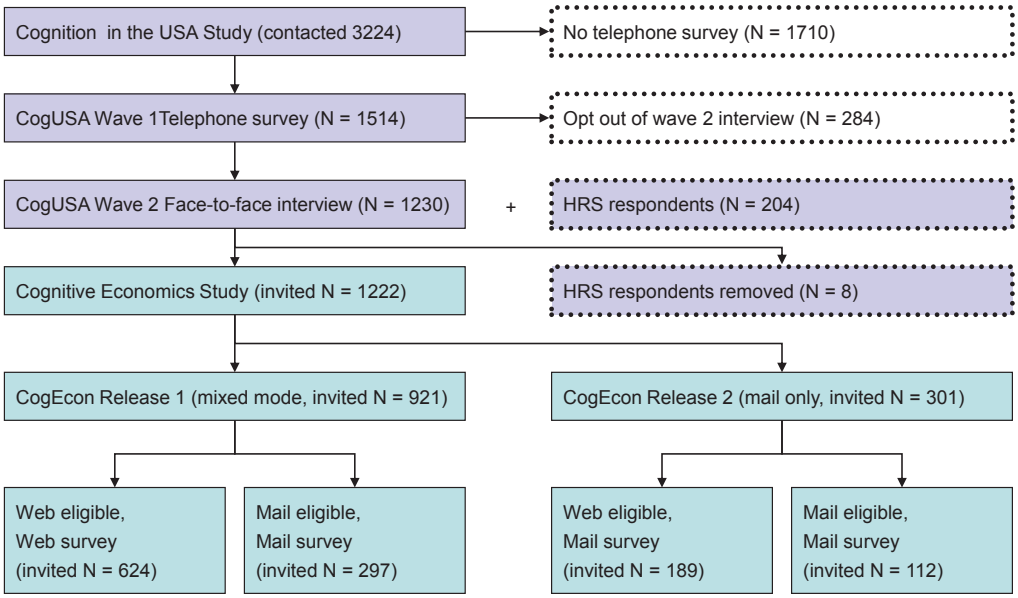
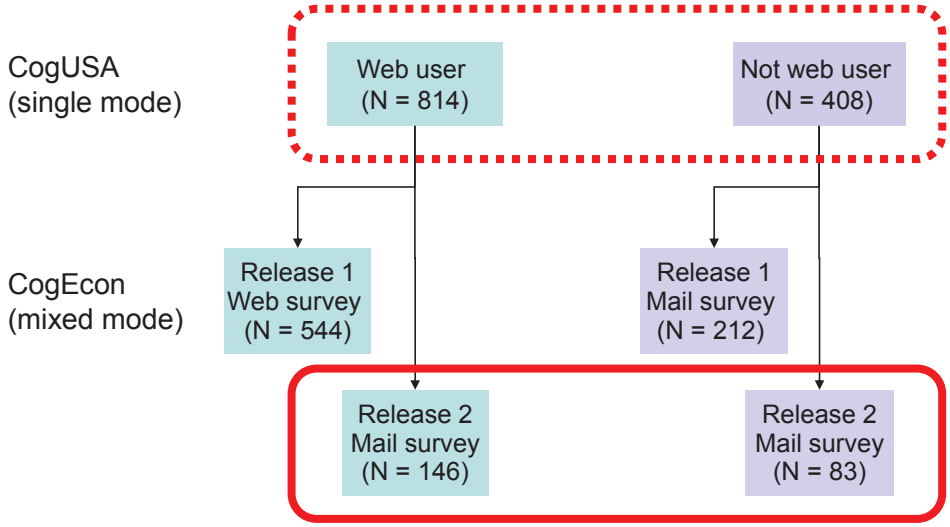


Figure 3: Web users and non-users on CogUSA and CogEcon



Each wave of CogUSA was implemented in the same mode for all respondents (waves 1 and 3 over the telephone; wave 2 in person). CogEcon fielded its 2008 survey by mail to some respondents and web for other users. Note that the 544 web users in release 1 include 30 respondents who submitted a mail questionnaire. These 30 either requested a mode switch or did not respond until we sent a final reminder with a paper survey.

Figure 4: Predicted probabilities of internet access

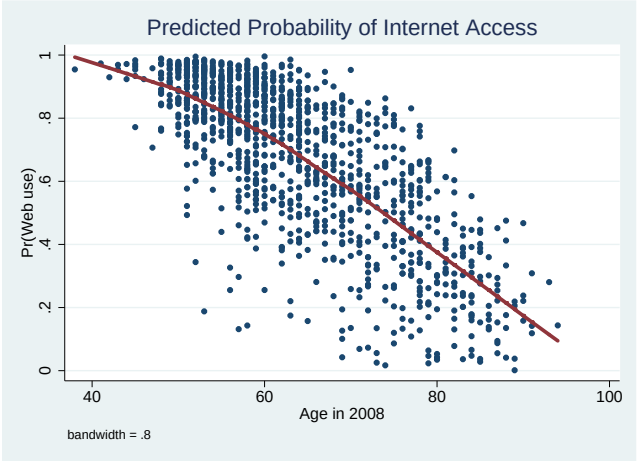


Figure 5: Densities of cognition scores, by internet access

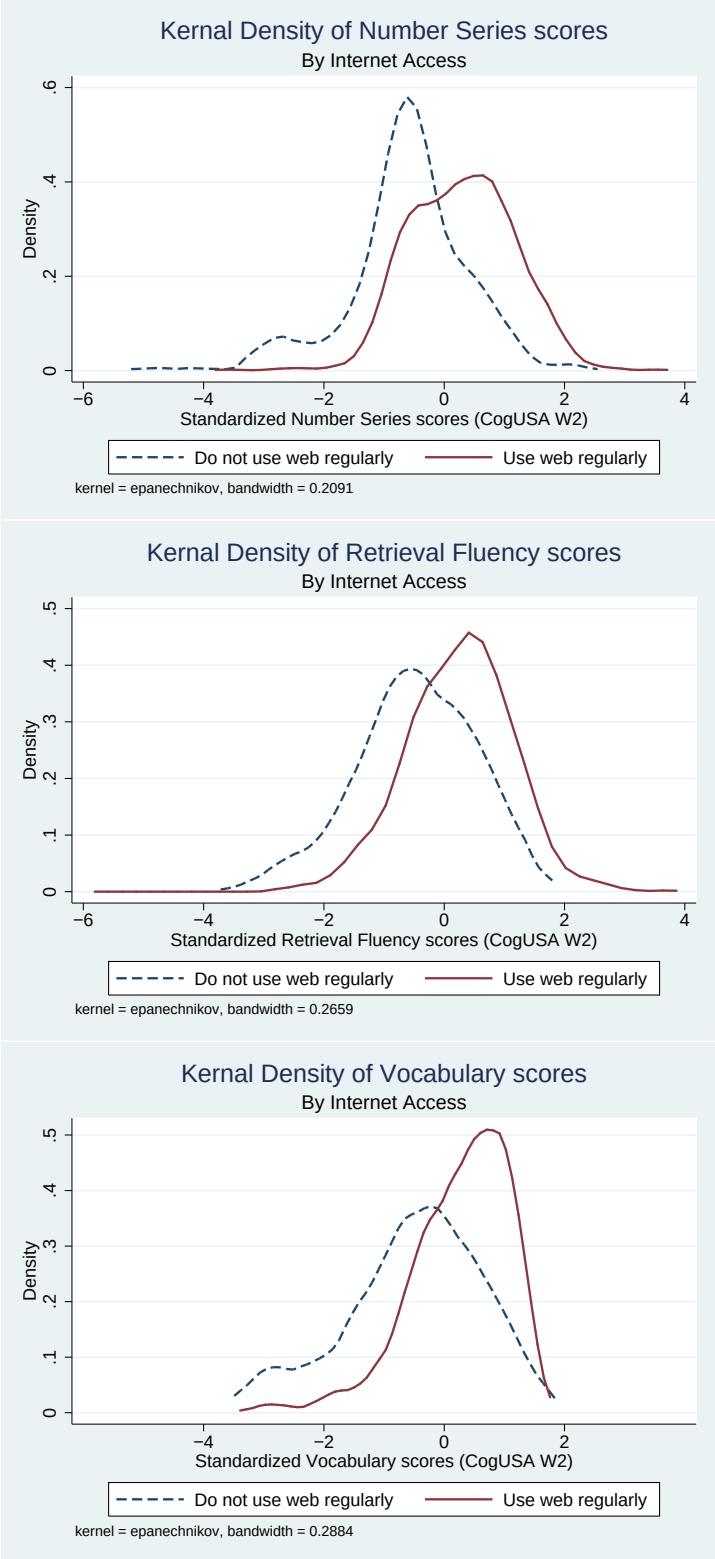


Figure 6: Life cycle pattern of fluid and crystallized intelligence

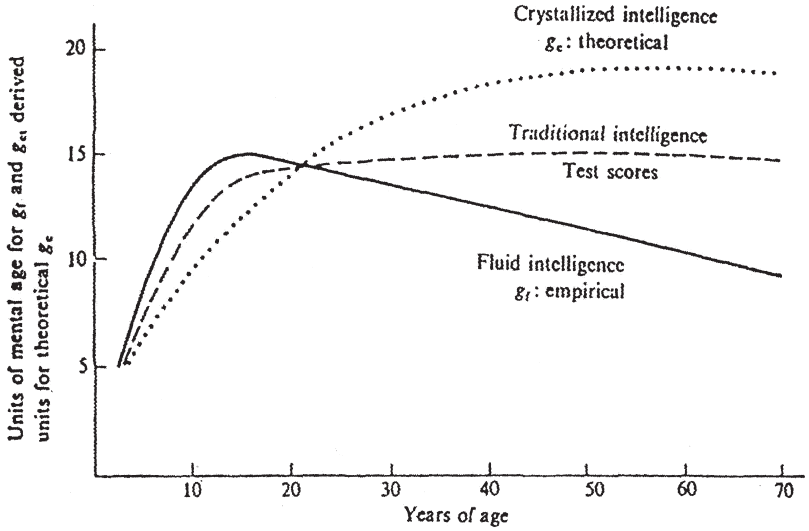


Figure 1. A theoretical description of life span curves of intellectual abilities. From *Intelligence: Its structure, growth and action* (p. 206) by R. B. Cattell, 1987, Amsterdam: North-Holland. Copyright 1987 by Elsevier Science Publishers. Reprinted with permission.

Figure from ?.

Figure 7: Age profile of standardized scores

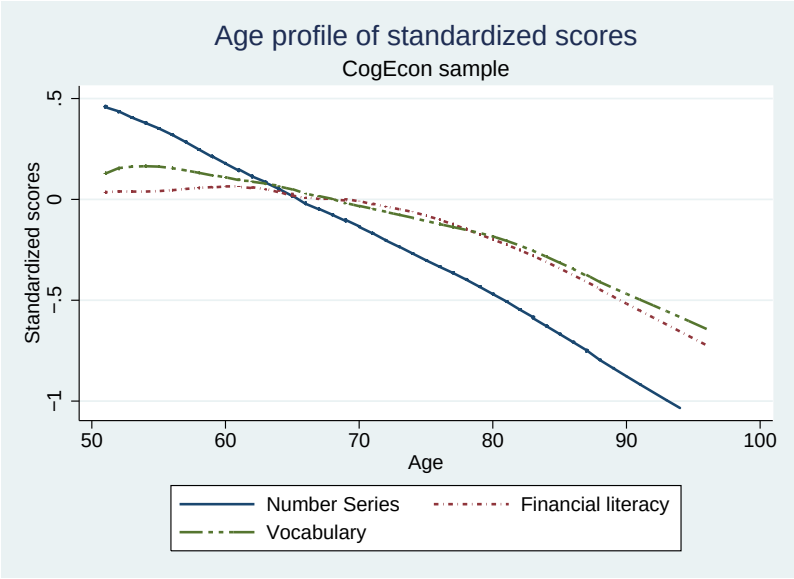


Figure 8: Age profiles of standardized scores, by internet access

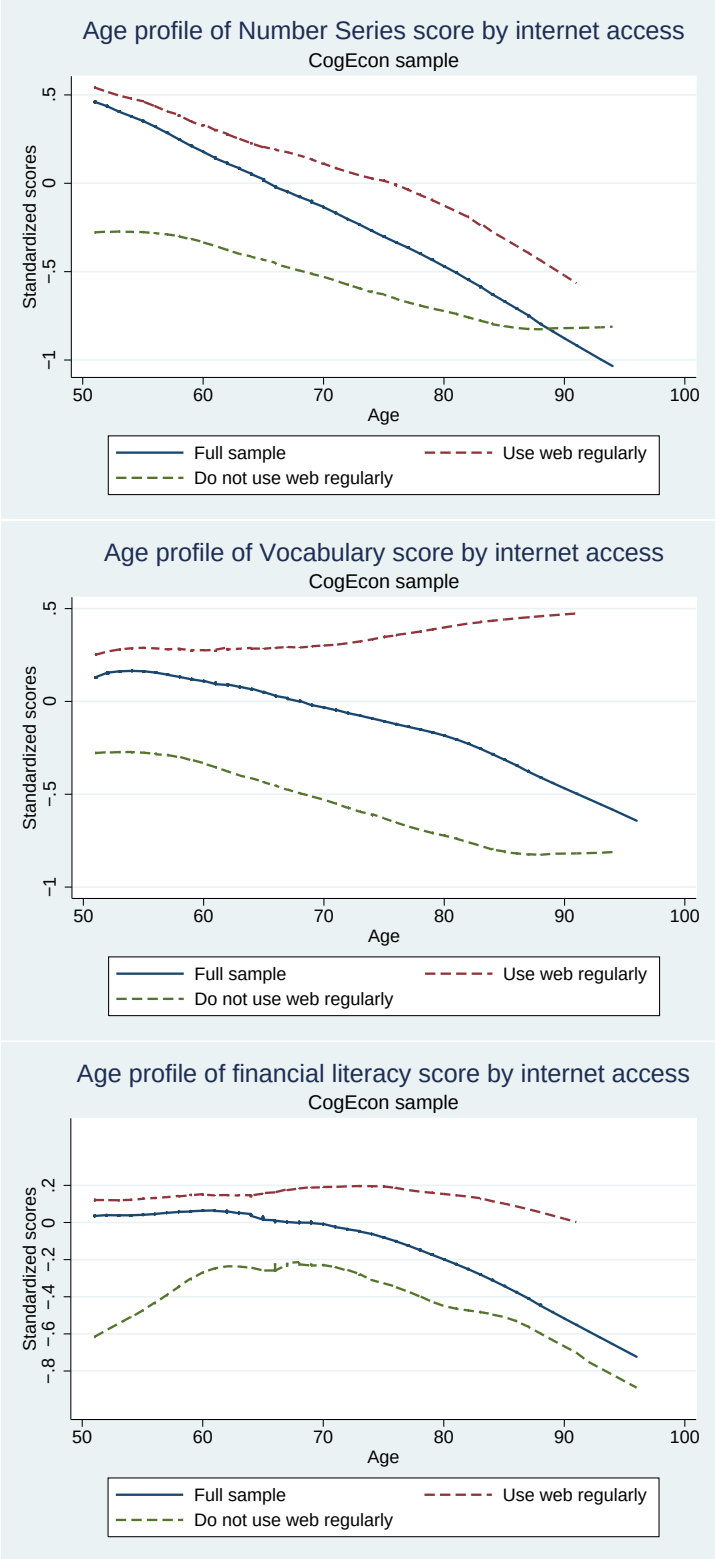


Figure 9: Age profiles of standardized scores, by education

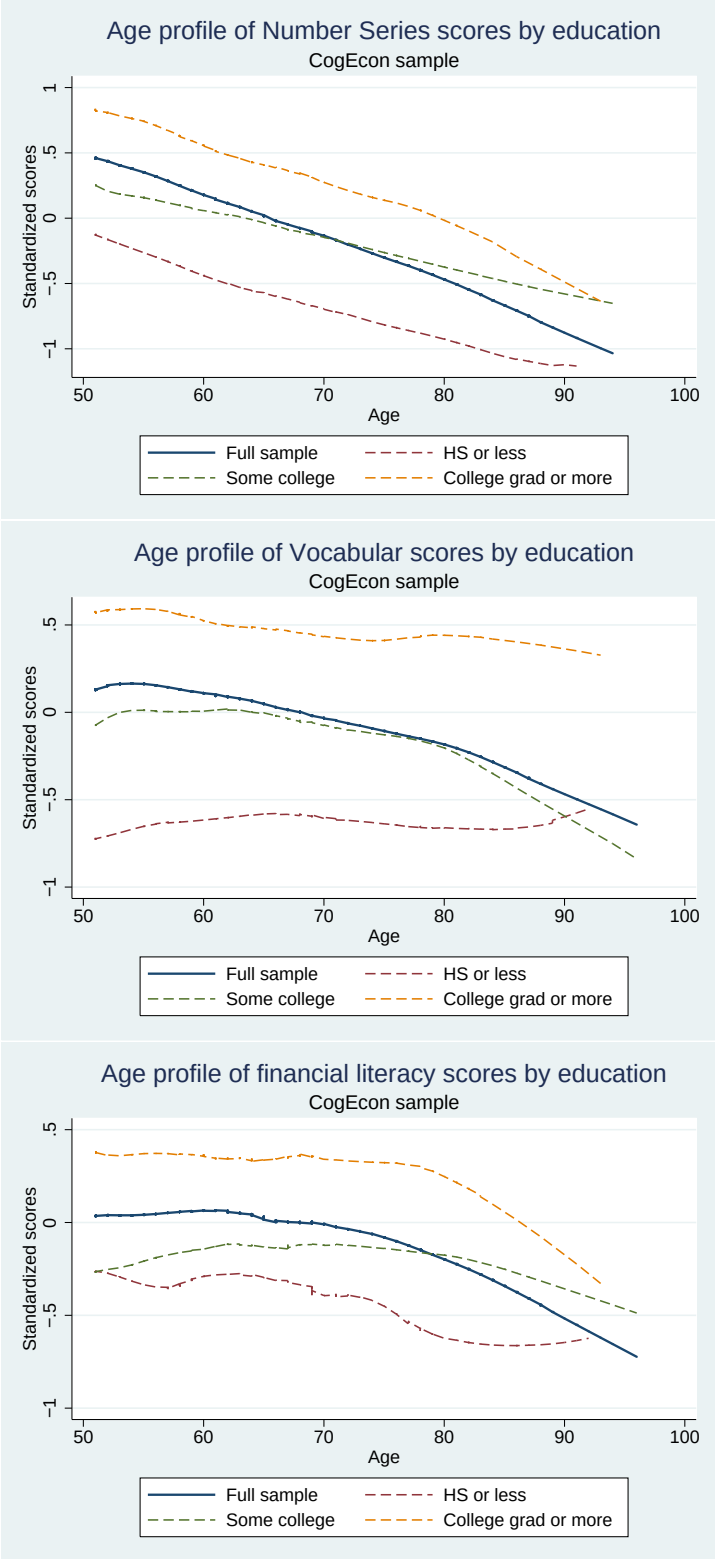


Table 1: Probit model of determinants of internet access - CogUSA and CogEcon

	(1)	(2)
Age	-0.01***	-0.01***
	(0.00)	(0.00)
Female	0.06*	0.06*
	(0.02)	(0.02)
Education	0.05***	0.02**
	(0.01)	(0.01)
Coupled	0.08**	0.05
	(0.03)	(0.03)
Number Series (standardized)		0.08***
		(0.02)
Retrieval Fluency (standardized)		0.02
		(0.01)
Vocabulary (standardized)		0.06***
		(0.01)
N	1207.00	1207.00

* significant at 5%; ** significant at 1%; *** significant at 0.1%

Dependent variable is 1 if the respondent uses the internet regularly, 0 otherwise. Average marginal effects reported. Robust standard errors in parentheses (couple-level clusters).

Table 2: Probit model of determinants of internet access - CogEcon only (full sample)

	(1)	(2)
Age	-0.01***	-0.01***
	(0.00)	(0.00)
Female	0.05	0.05*
	(0.03)	(0.02)
Education	0.05***	0.02**
	(0.01)	(0.01)
Coupled	0.08**	0.06*
	(0.03)	(0.03)
Number Series (standardized)		0.07***
		(0.02)
Retrieval Fluency (standardized)		0.01
		(0.01)
Vocabulary (standardized)		0.08***
		(0.01)
N	969.00	969.00

* significant at 5%; ** significant at 1%; *** significant at 0.1%

Dependent variable is 1 if the respondent uses the internet regularly, 0 otherwise. Average marginal effects reported. Robust standard errors in parentheses (couple-level clusters).

Table 3: Probit model of determinants of internet access, with income and wealth - CogEcon full sample

	(1)	(2)	(3)	(4)
Age	-0.012***	-0.009***	-0.010***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Female	0.048	0.058*	0.059*	0.063*
	(0.025)	(0.025)	(0.025)	(0.025)
Education	0.046***	0.014*	0.038***	0.012
	(0.006)	(0.006)	(0.006)	(0.006)
Coupled	0.089**	0.063*	0.070*	0.055
	(0.030)	(0.029)	(0.031)	(0.030)
Number Series (standardized)		0.058**		0.050**
		(0.019)		(0.019)
Retrieval Fluency (standardized)		0.017		0.015
		(0.014)		(0.014)
Vocabulary (standardized)		0.081***		0.079***
		(0.015)		(0.015)
Financial literacy (standardized)		0.023		0.017
		(0.014)		(0.014)
Log(Earnings)			0.009**	0.005
			(0.003)	(0.003)
Log(Net wealth)			0.013**	0.008
			(0.004)	(0.004)
N	943.000	943.000	943.000	943.000

* significant at 5%; ** significant at 1%; *** significant at 0.1%

Dependent variable is 1 if the respondent uses the internet regularly, 0 otherwise. Average marginal effects reported. Robust standard errors in parenthesis (couple-level clusters).

Table 4: Probit model of determinants of internet access, with income and wealth - CogEcon Release 2 only

	(1)	(2)	(3)	(4)
Age	-0.014***	-0.010***	-0.010**	-0.008*
	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.043	0.041	0.050	0.042
	(0.058)	(0.054)	(0.057)	(0.053)
Education	0.053***	0.014	0.043**	0.011
	(0.013)	(0.016)	(0.014)	(0.016)
Coupled	0.115	0.083	0.115	0.090
	(0.066)	(0.062)	(0.068)	(0.064)
Number Series (standardized)		0.116**		0.107**
		(0.037)		(0.038)
Retrieval Fluency (standardized)		0.019		0.023
		(0.033)		(0.033)
Vocabulary (standardized)		0.071*		0.068*
		(0.030)		(0.030)
Financial literacy (standardized)		0.010		0.012
		(0.032)		(0.031)
Log(Earnings)			0.014*	0.009
			(0.006)	(0.006)
Log(Net wealth)			0.006	0.000
			(0.010)	(0.010)
N	217.000	217.000	217.000	217.000

* significant at 5%; ** significant at 1%; *** significant at 0.1%

Dependent variable is 1 if the respondent uses the internet regularly, 0 otherwise. Average marginal effects reported. Robust standard errors in parentheses (couple-level clusters).

Table 5: Probit model of determinants of survey response

	(1) Release 1	(2) Release 2
Internet access	0.122***	0.047
	(0.032)	(0.060)
Age	0.003*	0.004
	(0.001)	(0.003)
Female	-0.015	0.006
	(0.026)	(0.047)
Education	0.002	0.010
	(0.007)	(0.013)
Number Series (standardized)	0.035*	0.020
	(0.018)	(0.033)
Retrieval Fluency (standardized)	0.015	0.028
	(0.015)	(0.033)
Vocabulary (standardized)	-0.013	-0.053
	(0.016)	(0.032)
Coupled	0.046	-0.033
	(0.029)	(0.061)
N	874.000	295.000

* significant at 5%; ** significant at 1%; *** significant at 0.1%

Average marginal effects reported. 30 web-eligible respondents from Release 1 who did not respond until a final reminder with an attached paper questionnaire are excluded. Robust standard errors in parentheses (couple-level clusters).

Table 6: Means of selected outcomes, with and without propensity score weights

	(1)		(2)		(3)		(4)	
	Full Sample	Web-mail	Web unadjusted		Web-adjusted (No cognition)		Web-adjusted	
	Mean	Diff.	Mean	Diff.	Mean	Diff.	Mean	Diff.
Diabetes	0.155	***	0.135	-0.020	0.156	0.002	0.148	-0.006
High blood pressure	0.484	***	0.428	-0.056	0.488	0.004	0.480	-0.003
Cancer	0.130	***	0.107	-0.023	0.140	0.010	0.126	-0.004
Lung disease	0.057	**	0.045	-0.012	0.075	0.018	0.062	0.005
Heart condition	0.187	***	0.143	-0.044	0.188	0.001	0.168	-0.018
Stroke	0.050	***	0.034	-0.016	0.057	0.007	0.048	-0.001
Arthritis	0.450	***	0.416	-0.034	0.475	0.025	0.457	0.007
Fallen last 2 years	0.299		0.273	-0.026	0.269	-0.030	0.290	-0.009
Ever smoked	0.523		0.521	-0.002	0.562	0.039	0.536	0.013
Currently smoke	0.200	**	0.170	-0.031	0.151	-0.049	0.156	-0.044
Memory disease	0.019	*	0.012	-0.007	0.011	-0.008	0.013	-0.006
Psychological problem	0.133		0.144	0.011	0.133	0.000	0.145	0.012
Trouble sleeping	2.495	*	2.520	0.025	2.513	0.018	2.506	0.011
Incontinence	0.211		0.200	-0.011	0.233	0.022	0.220	0.009
Work for pay	0.505	***	0.615	0.110	0.497	-0.008	0.530	0.025
Own home	0.895	***	0.916	0.021	0.896	0.001	0.893	-0.002
Retirement wealth	184	***	225	23%	189	3%	192	5%
Total wealth	909	**	1118	23%	996	-11%	1013	2%

Each cell is a separate estimates of the mean of the variable specified in the row. Columns specify what sample is used and what weights are used. For web-mail differences in column (1), * significant at 5%; ** significant at 1%; *** significant at 0.1%. Retirement wealth and total wealth are reported in thousands of dollars, and their respective full sample / web sample differences are reported as percents. Own home, retirement wealth (thousands of dollars), and total wealth (thousands of dollars) means were calculated using only the CogEcon sample. All others were calculated using the CogUSA sample with the sample sizes specified in the table.

A Summary of WJ-III Number Series and personality measures

Data collection in General Respondents completed a 35-40 minute telephone interview, followed by a three-hour face-to interview scheduled within 1-14 days after the initial telephone interview. The telephone interview comprised a series of questions to gather demographic characteristics, internet use, health status, and basic cognitive measures. The face-to-face interview was a much more in-depth assessment of cognitive functioning, as well as personality and a few other measures. The cross-battery set of cognitive measures included a series of tests from the Woodcock-Johnson III (WJ-III) tests of cognitive abilities and achievement.

Number Series The Number Series test in the W-JIII battery is a measure of fluid intelligence that measures quantitative reasoning (**?**). This ability involves reasoning with concepts that depend upon mathematical relationships. The task required the respondent to look at a series of numbers with a number missing from the series. The respondent needed to determine the numerical pattern, and then provide the missing number in the series. Answers were scored correct or incorrect for each item, and a standardized score (called a W-score) was computed based on WJ-III standard scoring (**?**).

Big Five Personality Inventory Personality refers to relatively stable characteristics of thought, affect, and behavior. In this study, we conceptualized personality in terms of the Big Five model of personality, which describes five broad personal traits: conscientiousness (being goal-directed, organized, and detail-oriented), agreeableness (having a tendency to get along easily with others), extroversion (enjoys social engagement and interacting with others), openness to experience (willing to try new things), and neuroticism (having a tendency to worry a lot). These five characteristics were measured via self report with the 44-item Big Five Inventory (BFI; **?**). Participants indicated the extent to which he/she agreed with

a series of statements that describe him/herself using a 5-point Likert-type response scale ranging from Strongly Disagree to Strongly Agree.

Need for Cognition Need for cognition is an individual difference variable defined by (**?**, p. 116) as "the tendency for an individual to engage in and enjoy thinking." Studies by Cacioppo and colleagues (e.g., **??**) have posited that individuals high or low in need for cognition make sense of their world and approach problem solving differently. For example, individuals high in need for cognition think about things, seek, acquire, and reflect on information, whereas those low in need for cognition prefer to obtain information from other sources, including other people, by making social comparisons, or using cognitive heuristics, rather than figuring things out for themselves. We measured need for cognition in this study using the 18-item short form measure validated by **?**. Participants responded to each item using a 5-point Likert-type response scale ranging from Strongly Disagree to Strongly Agree. Variables for analysis were constructed in two ways. First, we constructed a single, composite summary measure of all 18 items. Secondly, we constructed three separate dimensions of the need for cognition scale based on **?**. The three dimensions were (1) cognitive confidence (the extent to which one is confident about engaging in cognitive activities), (2) cognitive persistence (the extent to which one enjoys engaging in cognitive tasks), and (3) cognitive complexity (a tendency to prefer complex problems more than simple ones).