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Behavioral factors and long-run financial well-being

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Introduction

Questions about whether individuals and households adequately save, and adequately manage those savings, have long concerned researchers, policymakers and firms offering savings and retirement planning/products/services. These concerns are now more salient with the advent of 401(k) plans and the general trend toward defined contributions rather than defined benefits, and it has never been more important to understand what influences individual *decisions* about how much to save, where to allocate savings, how quickly to draw down savings, and myriad other influences on financial health leading up to and in retirement (Poterba, et al., 2007; Lusardi and Mitchell, 2014).

Over the last few decades, research at the intersection of economics and psychology has documented and modeled a rich taxonomy of “behavioral factors”—deviations from the classical economic specifications of preferences, decision-making rules and beliefs—that may help explain a wide variety of economic decisions and outcomes, including but not limited to wealth accumulation, savings and financial well-being in retirement (Chetty, 2015; DellaVigna, 2009; Kőszegi, 2014). Such factors include “present-bias,” failures to understand the benefits of compounding, biased beliefs that cloud proper stock market asset allocation decisions, and many others.[1]

Insights from this research have started to become important inputs for economists, policymakers and financial service providers interested in fostering the long-term financial health of those preparing for and entering retirement (Thaler and Benartzi, 2004; Benartzi and Thaler, 2007; Mullainathan and Thaler, 2000). Some examples are the proliferation of “nudge units” and other centers of applied behavioral social

[1] The list of references is too numerous to show here, but for a comprehensive discussion, see the PIs’ Research Dialogue [need reference or enter directly here].

sciences in both government agencies and private sector companies, the invoking of behavioral economics as a basis for changing default contribution rates or allocations to 401(k) plans, and a recent request for applications by the National Institutes of Health for work on the "identification and measurement of appropriate economic phenotypes…honed in behavioral and experimental studies."

That said, there are two important gaps in what we know about behavioral factors, retirement planning and long-term financial well-being.

First, how widespread is "being behavioral"—do relatively few or many people make decisions that deviate from classical economic norms? And which behavioral factors are most prevalent? Answering those questions require practical methods for eliciting multiple behavioral factors from large samples of individuals. Due to budget or time constraints, prior work has often measured one or a few such factors and/or elicited them in non-representative samples such as college students. Our literature reviews of direct elicitation work on 16 prominent behavioral factors ("B-factors") indicates that many biases have only been measured in non-representative samples. Nine of the 16 B-factors we consider lack even a single prevalence estimate from nationally representative U.S. data.

A second and equally important gap in what we know is understanding links between "being behavioral" and savings for retirement and wealth accumulation, as well as individuals' self-assessed level of satisfaction with their retirement preparedness. How impactful are behavioral factors in influencing retirement planning and outcomes? Most extant empirical studies measure just one or a few factors due to budget or methodological constraints, but do not link a full set of factors to outcomes.[2] The key is measuring a rich set of B-factors at the individual level, something that has yet to be done, and then aggregating those factors into a single "behavioral summary statistic" capturing how behavioral an individual is.

We provide new evidence on these questions for 16 B-factors. One set of B-factors relates to preferences: present-biased discounting (Read and van Leeuwen, 1998; Andreoni and Sprenger, 2012), loss aversion (Fehr and Goette, 2007), preference for certainty (Callen, et al., 2014), ambiguity aversion (Dimmock, et al., 2016), and choice inconsistency (Choi, et al., 2014). Other B-factors capture biased beliefs, biased perceptions and behavioral decision rules: two varieties of overconfidence (Moore and Healy, 2008), narrow bracketing (Matthew Rabin and Weizsäcker, 2009), exponential growth biases (Stango and Zinman, 2009; Levy and Tasoff, 2016), statistical fallacies (Dohmen, et al., 2009; Benjamin, Moore, and Rabin, 2013; Benjamin, Rabin, and Raymond, 2016), and limited attention/memory (Ericson, 2011). We selected B-factors by drawing on recent direct elicitation papers in top economics and finance journals, consulting with seminar and conference audiences during the design phase of the project, and making some allowances for tractability.[3]

We can elicit this large set of B-factors because we streamline standard direct elicitation methods by shortening, simplifying and combining tasks/questions. Streamlining elicitations saves costs/time and allows us to construct an unusually rich, person-level dataset capturing behavioral tendencies, demographics, other decision inputs and financial decisions/outcomes.

[2] Goda, et al. (2015), is an important exception, and the paper most similar to what the PIs propose in examining the prevalence and predictive power of multiple behavioral factors in national samples. They do so for a much smaller number of behavioral factors, as do Bruine de Bruin, Parker, and Fischoff (2007) and Li, et al. (2015), on convenience samples. Tanaka, et al. (2010), do lab-style elicitations for estimating loss aversion, present-bias, and probability-weighting for 181 Vietnamese villagers, and link those elicitations to survey data (on income, etc.), but they consider each behavioral factor independently.

[3] This paragraph cites the papers that had the greatest influence on our elicitation designs. With respect to drawing the line on what we did and did not seek to measure, some examples of tractability considerations are that we could not devise methods for eliciting projection bias or confirmation bias that seemed feasible given our budget constraint and other measurement priorities. If unconstrained, we also would have elicited social preferences; given constraints this seemed like a natural line of demarcation, as in, e.g., Gabaix (2014, 2017)which is a less than fully attentive and rational version of the traditional max operator. The agent builds (as economists do.

We implement our elicitations as part of six online survey modules administered to a nationally representative U.S. sample of 1,400+ participants in RAND's American Life Panel (ALP) in 2014-15 and 2017. The two modules take about 60 minutes per respondent in total.

Previewing our key results, we find that most B-factors are indeed quite prevalent, with some deviation from the "classical norm" exhibited by at least 50% of the sample for 11 of the 16 B-factors. High prevalence is not simply an artifact of how we measure it. We actually classify fewer people as behavioral than prior studies using comparable elicitation methods on representative U.S. samples, for 5 of the 7 B-factors with prior comparable studies.[4] Our main takeaways on the first question are that B-factors are widespread enough in the general population to motivate continued scrutiny, and that our streamlined methods are useful for eliciting them.

Turning to the second question, we find that cross-sectional heterogeneity in B-factors does in fact correlate with outcomes, and that generally speaking, "being behavioral" reduces individual's self-assessed financial well-being, as well as their "hard" measures of retirement preparedness such as wealth and stock market participation. Our main takeaway here is that B-factors do have economically substantial links to long-run financial well-being.

In future work, we plan to ask whether there are common factors that drive "being behavioral"; whether and how the use of financial advice mitigates the effects of being behavioral, or the links between behavioral factors and financial well-being; and a series of other questions. All of these investigations should yield new empirical facts that can shape policy, research and practice.

Research design and data

Our data come from the RAND American Life Panel (ALP). The ALP is an online survey panel that was established in collaboration between RAND and the University of Michigan to study methodological issues of Internet interviewing. Since its inception in 2003, the ALP has expanded to approximately 6,000 members aged 18 and older.

The ALP takes great pains to obtain a nationally representative sample, combining standard sampling techniques with offers of hardware and a broadband connection to potential participants who lack adequate Internet access. ALP sampling weights match the distribution of age, sex, ethnicity, and income to the Current Population Survey.

Panel members are regularly offered opportunities to participate in surveys, the purposes of which range from basic research to political polling. More than 400 surveys have been administered in the ALP, and data become publicly available after a period of initial embargo. This opens up opportunities for future work linking our data to other modules.

Speaking broadly, our goal was to design elicitation methods that robustly yield data on the widest possible range of behavioral factors at a reasonable cost. We also sought to use elicitation methods that could be employed online rather than in-person, given that in-person elicitation typically comes at higher cost.

In consultation with ALP staff, we divided our elicitations and other survey questions into four thirty-minute modules and two shorter modules. This strategy adhered to ALP standard practice of avoiding long surveys (based on staff findings that shorter surveys improve both response rates and quality), and allowed us to evenly disburse the more demanding tasks across the two modules. Per standard ALP practice, we paid panelists $10-$20 per completed module.

After extensive piloting, the ALP fielded the first part of our instrument as ALP module 315, sending standard invitations to panel participants aged 18-60 in November 2014. Given our target of 1,500 respondents, the ALP

[4] By our accounting, the 7 B-factors with a nationally representative prevalence estimate for the United States in prior work are: money discounting biases (Bradford, et al., 2014; Goda, et al., 2017), discounting biases (Barcellos and Carvalho, 2014), loss aversion (Hwang, 2016), narrow bracketing (Gottlieb and Mitchell, 2015; Rabin and Weizsäcker, 2009), ambiguity aversion (Dimmock, et al., 2016), debt-side exponential growth bias (Stango and Zinman, 2009, 2011), and asset-side exponential growth bias (Levy and Tasoff, 2016; Goda, et al., 2017).

sent 2,103 initial invitations. The invitation remained open until March 2015, but most respondents completed surveys during the first few weeks after the initial invitation, as is typical in the ALP. 1,515 individuals responded to at least one of our questions in module 315, and those 1,515 comprise the sample for our study and the sample frame for the next parts of our instrument.

The ALP fielded the second part of our instrument as ALP module 352, sending invitations to everyone who responded to module 315, starting in January 2015 (to avoid the holidays), with a minimum of two weeks in between surveys. We kept that invitation open until July 2015. 1,427 individuals responded in part or whole to that second module. The third module was a short follow-on to the second, administered the next day.

We then re-fielded the same three surveys to as many of those panelists as possible. These second surveys were fielded in October and November 2017 as modules 472-474, and yielded useful data for roughly 800 of the original 1,515 panelists. Those data are in the process of being analyzed, and this report therefore focuses on the earlier sets of data.

Measuring B-Factors and other individual characteristics

In all, we conduct elicitations of 16 potentially behavioral factors. Given our goals of directly eliciting useful measures of B-factors without breaking the bank, we prioritize elicitation methods that have been featured recently in top academic journals and were short and simple enough (or could be so modified) to fit into modules that would also allocate substantial survey time to measuring other decision inputs and financial well-being.

Table 1 summarizes our list of B-factors, definitions, elicitation methods and their key antecedents.[5] Deviations from classical norms may be unidirectional, as in the case of choice inconsistency: someone either chooses consistently with the General Axiom of Revealed Preference, or does not. For other B-factors, deviations from classical norms are bidirectional. For example, in the case of discounting, one can be either present-biased or future-biased relative to being time-consistent (unbiased). For each bidirectional B-factor, we define a "standard" direction based on what has been more commonly observed or cited in prior work; e.g., present-biased discounting (with future-bias classified as non-standard and time-consistent as unbiased), overconfidence in performance (with underconfidence as non-standard and accurate assessment of one's own performance as unbiased), and underestimating exponential growth (with overestimating as non-standard and accurate estimation as unbiased).

The modules also elicit rich measures of cognitive skills and demographics, such as gender, income and education.

Result #1: B-factors are prevalent

Are B-factors prevalent in a broad population? As noted at the outset, our literature reviews turned up U.S. population estimates for only a few of the B-factors we consider. The main question here is qualitative: does the overall pattern of evidence suggest that behavioral tendencies are more than just isolated anomalies?

Figure 1 and Table 2 show that our B-factors are indeed prevalent.[6] Some deviation from classical norms is indicated by at least 50% of the sample for 9 of the 16 factors for which we can estimate prevalence. In a more detailed working paper, we impose more-stringent thresholds on what indicates a behavioral bias, counting only economically large deviations (defining "large" in various ways) from classical norms, and find that most B-factors remain prevalent (e.g., exhibited by >20% of the population).

The "standard" directional bias emphasized by prior literature is indeed more prevalent in our data, in 6 of the 7 B-factors where we capture bidirectional

[5] Interested readers can refer to our Research Dialogue for further details.

[6] Results are basically unchanged if we use the ALP's population weights.

biases and there is a clear standard.[7] But in fact, and consistent with prior work, we find that underestimation of compound growth or decline is far more common than overestimation. Where comparable, our estimates of prevalence are in-line with prior findings, for the nine B-factors for which we could find prior studies on nationally representative samples.

Result #2: Using a summary measure ("B-count"), almost everyone is "Behavioral"

Here we define a key new construct, the "B-count": the sum of how many (standard and/or nonstandard) B-factor indicators an individual displays. It is, in casual parlance, a measure of "how behavioral" an individual is. Our primary B-count counts any deviation as behavioral, although we also consider other definitions.[8] The maximum possible B-count is 16.[9]

Table 3 shows overall statistics for our sample of individuals. The median B-count, considering all possible deviations, is 9 with a standard deviation of 2.5. Nearly every consumer exhibits at least one deviation (100% with rounding), and the 10th percentile has a B-count of 6. Counting only standard-direction deviations among the bidirectional B-factors produces only slightly lower B-counts than counting any deviation (Column 2 vs. Column 1).

The shapes of these simple summary statistics have important implications. First, they suggest that most consumers have behavioral tendencies to some meaningful extent, ratifying the focus of many policymakers and researchers on behavioral tendencies and how to treat them. Second, they bear directly on key assumptions and inputs to theoretical models that incorporate parameters measuring how common is "being behavioral."

Within-group differences in B-counts dwarf cross-group differences

Figures 2-5 show our "standard" B-counts broken out for groups at the opposite ends of the income, education, gender, and cognitive skills distributions. The B-count varies substantially within all of the sub-groups we examine. Being behavioral is not confined to those with low cognitive skills, or to males, or to low-income or low-education individuals. In most cases the median level of B-count is similar across splits, and the most striking pattern here is that any cross-group differences are dwarfed by the within-group variation.

What that tells us is that B-counts—or "being behavioral"—do not simply reflect the influence of things like education, or income, or even "smarts" defined broadly. Even if one takes a group of people who look pretty similar on all those other metrics, there will be significant variation within that group in how behavioral different people are. This encourages us that we are not simply looking at a different "part of the elephant" that really captures the same underlying phenomenon, and that it is worth exploring relationships between B-counts and financial well-being.

Result #3: B-factors exhibit important links to financial well-being and retirement preparedness

The main litmus test for whether B-factors and B-counts prove useful is whether they are linked to financial well-being. A simple way to examine that is by looking at links between our B-counts and financial well-being.

[7] Both Gambler's Fallacies—hot-hand and cold-hand—have attracted substantial researcher attention, and so for the purposes of estimating prevalence, we do not think there is a clear standard directional bias. For the purposes of estimating links to financial condition, we focus more on the hot-hand bias.

[8] A previous working paper version examined the threshold-for-deviation question in detail, with little change in the key inferences.

[9] We have 24 indicators across 16 behavioral factors, but factors with bidirectional deviations allow for a maximum of one deviation per individual—bidirectional deviations are mutually exclusive within-person.

Our surveys measure rich data on financial choices and outcomes. We construct nine indicators of financial condition from 15 survey questions, 14 of which are in module 315. The questions elicit information on net worth, financial assets, recent savings behavior, household distress as measured by recent events (missed housing utility payments, forced moves, postponed medical care, hunger), and summary self-assessments of savings adequacy, financial satisfaction and financial stress. We drew the content and wording for these questions from other American Life Panel modules and other surveys (including the National Longitudinal Surveys, the Survey of Consumer Finances, the National Survey of American Families, the Survey of Forces, and the World Values Survey).

We then take those measures and use them to construct a single measure of well-being based on how many of the 9 indicators an individual displays. This single measure varies from 0 (lowest financial well-being) to 1 (highest financial well-being).

Figure 6 groups individuals with different B-counts into four bins (0 to 5, 6 to 9, 10 to 11, and 12+) and asks how financial well-being varies across those bins. Because income is a strong determinant of well-being, we further stratify into three categories of low/medium/high income.

For every income category, there is a clear negative relationship: as individuals become "more behavioral," their financial well-being is lower. This is true for low-income individuals, for middle-income individuals, and for high-income individuals. The decline in financial well-being is quite strong and leads to one conclusion: behavioral factors are strongly and negatively linked to overall financial well-being.

While we do not show the results, if we break out the individual components of well-being (like self-assessed retirement preparedness, or savings, or wealth), then the results are still quite strong.

Conclusion

Despite broad and growing influence, behavioral economics has lacked nationally representative evidence on basic empirical questions, and we provide methods and data for addressing many of them. Behavioral biases are prevalent, not anomalous. They are distinct features of consumer decision-making, not merely proxies for unmeasured aspects of demographics, or cognitive abilities.

Most important, they are correlated with short- and long-run financial well-being in ways predicted by theory, and are not neutralized by market forces, learning, or other factors.

This paper only begins to tap the potential of the new elicitation methods and dataset described herein. On the elicitation side, direct comparisons between our elicitations and standard ones would refine approaches to lowering the cost of measuring B-factors. Our methods are suitable for collecting data in a variety of settings and thus can be used to expand the evidence base on B-factors. In particular, our streamlined elicitations could be integrated into established representative and large-sample household surveys, one B-factor at a time. This would increase power for estimating relationships between behavioral biases and field choices/outcomes.

In terms of the data used here, we are already at work exploring relationships among B-factors, and how to efficiently measure and summarize information on behavioral and other decision inputs. Beyond there are many possibilities for exploiting the panel, multi-topic architecture of the ALP to explore relationships between our behavioral variables, covariates, and outcomes in yet more domains. That work could include more detailed consideration of behavioral theories, including structural models, than we undertake in this paper.

Pushing further to map links between the multitude of behavioral factors and outcomes will improve understanding about consumer choice, market functioning, and policy design across the many domains in which behavioral economics has taken hold—energy, household finance, labor, health and others.

Figure 1. The prevalence of individual "behavioral factors"

These are the "standard" biases from Table 2.

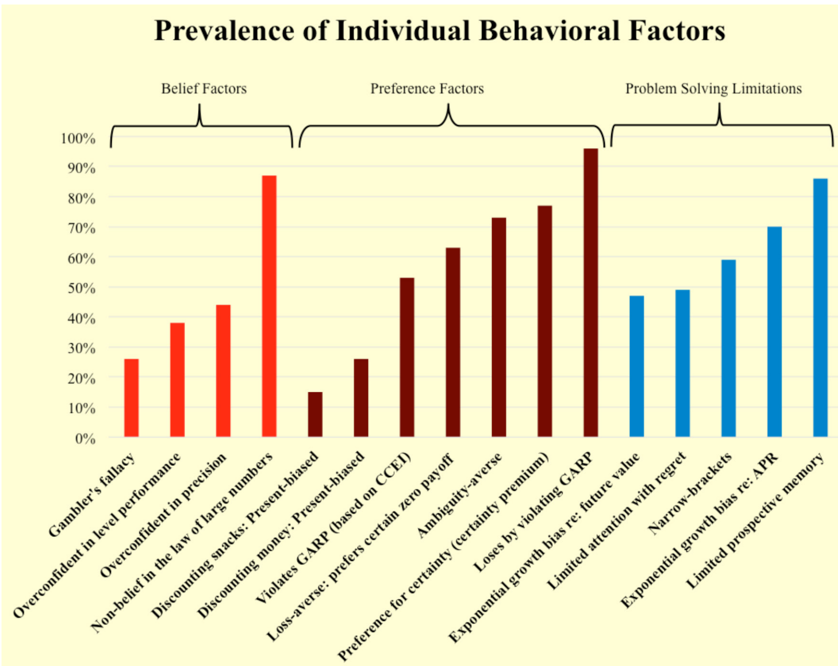


Figure 2. B-counts by "high" and "low" education levels

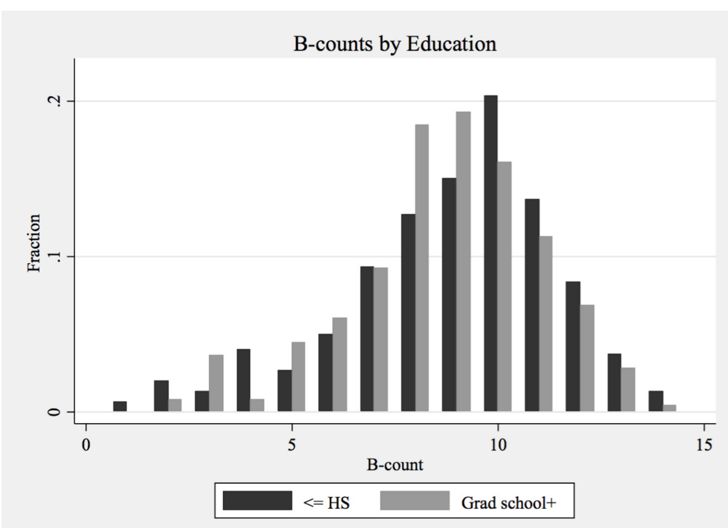


Figure 3. B-counts by gender

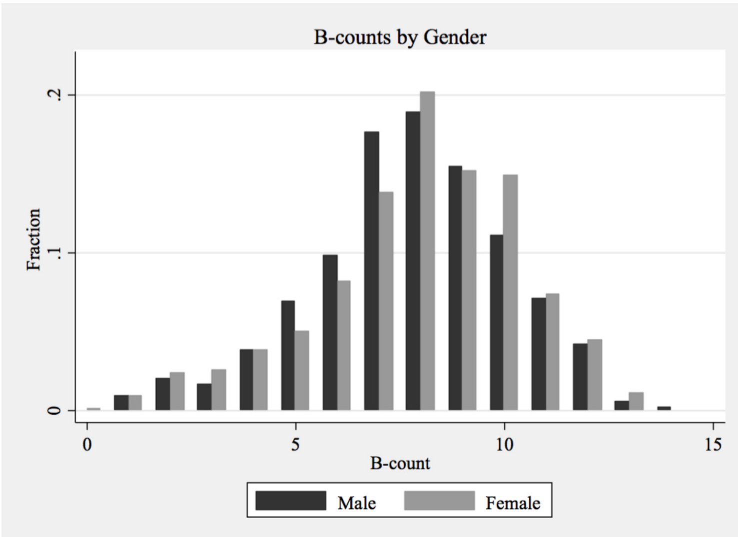


Figure 4. B-counts by high and low quartiles of cognitive ability

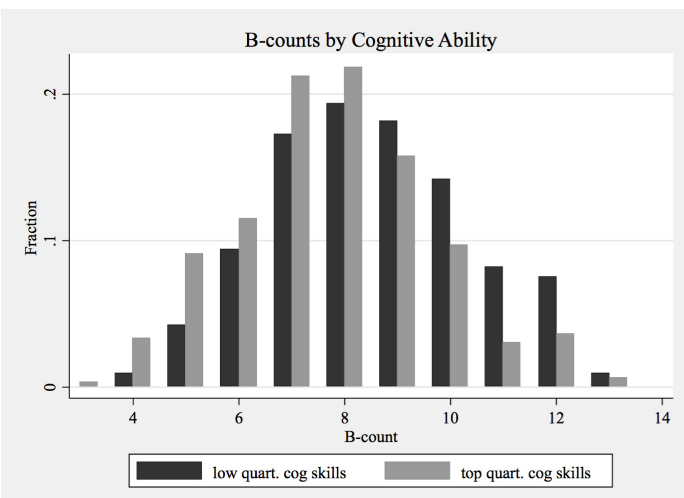


Figure 5. B-counts by high and low income quartiles

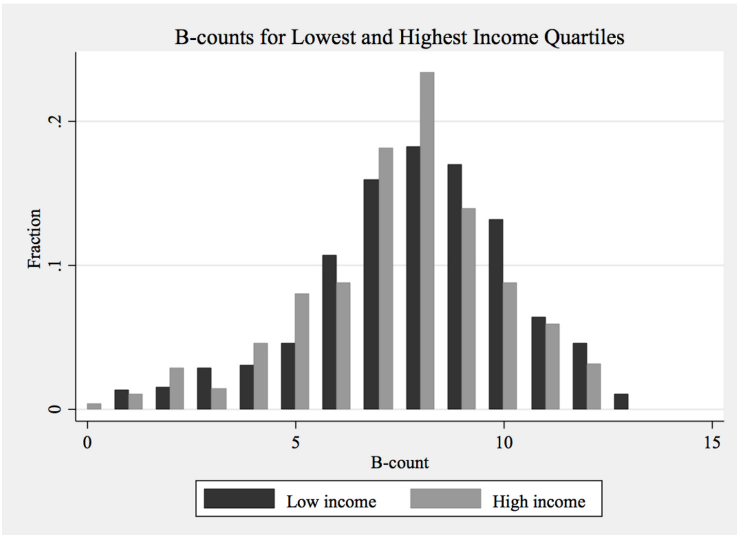
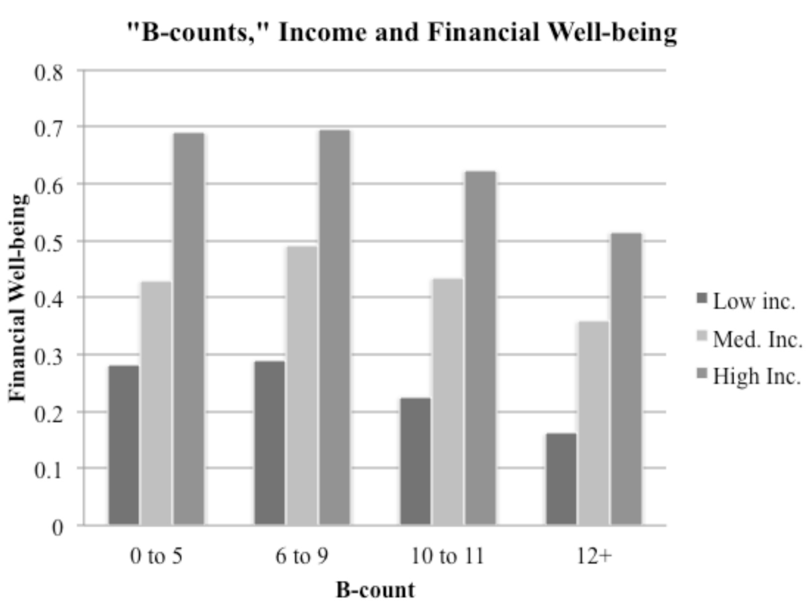


Figure 6. Links between B-counts, income and financial well-being



Well-being captures retirement savings, wealth, self-assessed retirement preparedness and other factors. Well-being varies from 0 to 1, with 1 being better financial well-being.

Table 1. Research design: Eliciting data on multiple behavioral factors, and defining behavioral bias indicators

B-factor name: key antecedents	Elicitation method description	Behavioral bias indicator(s), "standard" deviation direction in bold
Time inconsistent discounting of money: Andreoni & Sprenger (2012), Barcellos & Carvalho (2014)	Convex Time Budget. 24 decisions allocating 100 tokens each between smaller-sooner and larger-later amounts; decisions pose varying start dates (today vs. 5 weeks from today), delay lengths (5 or 9 weeks) & savings yields.	**Present-biased: discounts more when sooner date is today** Future-biased: discounts more when sooner date is 5 weeks from today
Time inconsistent discounting of snacks: Read & van Leeuwen (1998), Barcellos & Carvalho (2014)	Two decisions between two snacks: healthier/ less-delicious vs. less healthy/more delicious. Decisions vary only in date snack is delivered: now, or 5 weeks from now.	**Present-biased: choose less healthy today, healthy for 5 weeks from now** Future-biased: choose healthy for today, less healthy for 5 weeks from now
Violates General Axiom of Revealed Preference: (and/or dominance avoidance) Choi, et al., (2014)	Decisions from 11 different linear budget constraints under risk. Subjects choose a point on the line, then the computer randomly chooses whether to pay the point value of the x-axis or the y-axis.	**Violates GARP: potential earnings wasted per CCEI>0** **Violates GARP and/or dominance avoidance: potential earnings wasted per combined-CCEI>0**
Certainty premium: Callen, et al., (2014)	2 screens of 10 choices each between two lotteries, one a (p, 1-p) gamble over X and Y > X , (p; X, Y), the other a (q, 1-q) gamble over Y and 0, (q; Y, 0). Y=$450, X=$150, q ϵ[0.1, 1.0], p=0.5 on one screen and 1.0 on the other.	**Preference for certainty: certainty premium (CP) >0** Cumulative prospect theory: certainty premium (CP)<0
Loss aversion/small-stakes risk aversion: Fehr & Goette (2007)	Two choices. Choice 1: between a 50-50 lottery (win $80 or lose $50), and $0. Choice 2: between playing the lottery in Choice 1 six times, and $0.	**Loss aversion: choosing the certain $0 payoff in one or more choices.**
Narrow bracketing: Rabin & Weizsacker (2009)	Two tasks of two decisions each. Each decision presents the subject with a choice between a certain payoff and a gamble. Each decision pair appears on the same screen, with an instruction to consider the two decisions jointly.	**Narrow-bracketing: making a choice that is dominated given implications of an earlier decision, on one or both**
Ambiguity aversion: Dimmock, et al., (2016)	Two questions re: a game where win $500 if pick green ball. 1. Choose between bag with 45 green-55 yellow and bag with unknown mix. 2. If chose 45-55 bag, how many green balls in 45-55 bag would induce switch.	**Ambiguity Aversion: prefers bags with 45 green to bag with unknown mix.**
(Over)confidence in performance: Larrick, et al., (2007), Moore & Healy (2008)	How many of the last 3 questions (the ones on the disease, the lottery and the savings account) do you think you got correct?"	**Overconfidence in perform: self-assessment > actual score** Under-confidence in perform: self-assessment < actual score
Overconfidence in relative performance: Larrick, et al., (2007), Moore & Healy (2008)	"... what you think about your intelligence as it would be measured by a standard test. How do you think your performance would rank, relative to all of the other ALP members who have taken the test?"	**Greater diff between self-assessed and actual rank indicates more overconfidence. "Overconfident" = overconfidence above median (no precise cardinal)**
Overconfidence in precision: Larrick, et al., (2007), Moore & Healy (2008)	Questions about likelihoods of different numeracy quiz scores and future income increases.	**Overconfidence in precision: responds 100% to one or both questions**

Table 1 (continued). Research design: Eliciting data on multiple behavioral factors, and defining behavioral bias indicators

B-factor name: key antecedents	Elicitation method description	Behavioral bias indicator(s), "standard" deviation direction in bold
Non-belief in the law of large numbers (NBLLN): Benjamin, Moore, and Rabin (2013)	Question re: percent chances that, among 1,000 coin flips, the # of heads will fall in ranges [0, 480], [481, 519], and [520, 1000]. NBLLN = distance between response for	Overestimates convergence to 50-50: responds with>78% **Underestimates convergence to 50-50: responds with<78%**
Gambler's fallacies: Benjamin, Moore, and Rabin (2013)	"Imagine that we had a computer "flip" a fair coin... 10 times. The first 9 are all heads. What are the chances, in % terms, that the 10th flip will be a head?"	**Hot-hand fallacy: responds with >50%** Cold-hand fallacy: responds with <50%
Exponential growth bias (EGB), debt-side: Stango & Zinman (2009; 2011)	Survey first elicits monthly payment respondent would expect to pay on a $10,000, 48-month car loan (this response defines the actual APR). Then elicits perceived APR implied by that payment.	**Underestimates EG: actual APR>perceived APR** Overestimates EG: actual APR<perceived APR
Exponential growth bias (EGB), asset-side: Banks, et al., (2007)	Elicits perceived future value of $200, earning 10% annual, after two years.	**Underestimates EG: perceived FV<actual FV=$242** Overestimates EG: perceived FV>actual FV=$242
Limited attention: Author-developed	Four questions re: whether subject's finances would improve with more attention given the opportunity cost of attention, with questions varying the types of decisions: day-to-day, medium-run, long-run, or choosing financial products/services.	**Limited attention: Indicates regret about paying too little attention, on one or more of the four questions**
Limited prospective memory: Ericson (2011)	The ALP will offer you the opportunity to earn an extra $10...This special survey has just a few simple questions but will only be open for 24 hours, starting 24 hours from now...please tell us now whether you expect to do this special survey."	**Limited memory: Says will complete task but does not complete**

The Data Appendix provides additional details on measuring individual behavioral factors. "Standard" deviation direction, for bidirectional B-factors, is the direction typically theorized/observed in prior work to harm financial condition. "CCEI" = Critical Cost Efficiency Index..

Table 2. Prevalence and missing values for B-factors and their directional biases

B-factor and bias (standard direction in bold)	Share biased, conditional on repsonse	Missing detail		
		Survey nonresponse	Item nonresponse	Responded not usable
Time-inconsistent discounting money: Present-biased	**0.26**	0.00	0.06	0.00
Time-inconsistent discounting money: Future-biased	0.36			
Time-inconsistent discounting snacks: Present-biased	**0.15**	0.06	0.02	0.00
Time-inconsistent discounting snacks: Present-biased	0.07			
Violates GARP (based on CCEI)	**0.53**	0.06	0.10	0.00
Violates GARP (with dominance avoidance)	**0.96**	0.06	0.10	0.00
Certainty premium: >0=Preference for certainty type	**0.77**	0.00	0.03	0.28
Certainty premium: <0=Cumulative prospect theory type	0.23			
Loss-averse: prefers certain zero payoff	**0.63**	0.00	0.00	0.00
Narrow-brackets	**0.59**	0.00	0.02	0.00
Ambiguity-averse	**0.73**	0.06	0.03	0.07
Confidence in level performance: Overconfident	**0.38**	0.06	0.03	0.07
Confidence in level performance: Under-confident	0.11			
Overconfident in precision	**0.44**	0.06	0.04	0.00
Overconfident in relative performance	**0.50**	0.06	0.04	0.00
Non-belief in the law of large numbers: Underestimates convergence	**0.87**	0.06	0.03	0.00
Non-belief in the law of large numbers: Overestimates convergence	0.13			
Gambler's fallacy: hot hand	0.14	0.06	0.02	0.00
Gambler's fallacy: cold hand	0.26			
Exponential growth bias, loan-side: Underestimates APR	**0.70**	0.00	0.05	0.32
Exponential growth bias, loan-side: Overestimates APR	0.27			
Exponential growth bias, asset-side: Underestimates future value	**0.38**	0.06	0.03	0.00
Exponential growth bias, asset-side: Overestimates future value	0.07			
Limited attention	**0.49**	0.00	0.02	0.00
Limited memory	**0.86**	0.06	0.02	0.02

Unit of observation is the individual respondent, and missing shares are relative to the full sample size of 1,515. Section 1-C provides some details on measuring individual behavioral factors and classifying directional biases as standard vs. non-standard; see the Data Appendix for additional details. "GARP" = General Axiom of Revealed Preference. "CCEI" = Critical Cost Efficiency Index. Proportion exhibiting relative overconfidence is 50% by construction, since our elicitation does not produce a clear cardinal measure (as detailed in Data Appendix Section H). "Share biased" is conditional on non-missing values. "Survey nonresponse" indicates panelists who took our first module but not our second. "Item nonresponse" can occur on either module. The large "unusable" share for the Certainty Premium is partly due to respondents who do not switch on the multiple price lists; this is a limitation of the elicitation rather than an indication of low-quality responses (Data Appendix Section D). The large unusable share for EGB loan-side is due largely to responses that imply a zero APR (Data Appendix Section L).

Table 3. Summary statistics for the "B-count" at the level of the individual

	Indicators	
	All	Standard
"B-count" = count of behavioral indicators (N=1,511)		
max(observed)	15	14
min(observed)	1	0
proportion with any behavioral indicator	1.00	1.00
mean	9.05	7.90
SD	2.46	2.40
10th percentile	6	5
25th percentile	8	7
50th percentile	9	8
75th percentile	11	10
90th percentile	12	11

Notes: B-count measures how many "behavioral factors" from Tables 1/2 an individual in our surveys displays.

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