Complementary Cognitive Capabilities, Economic Decision-Making, and Aging

Ye Li[1,2], Martine Baldassi[2], Eric J. Johnson[2], and Elke U. Weber[2]

[1] University of California, Riverside, School of Business Administration

[2] Center for Decision Sciences, Columbia University

Address for correspondence:

Ye Li   Email: ye.li@ucr.edu
University of California, Riverside   Tel: 951.827.3694
Anderson Hall
900 University Avenue
Riverside, CA 92521

Abstract

Fluid intelligence decreases with age, yet evidence about age declines in decision-making quality is mixed: Depending on the study, older adults make worse, equally good, or even better decisions than younger adults. We propose a potential explanation for this puzzle, namely that age differences in decision performance result from the interplay between two sets of cognitive capabilities that impact decision making, one in which older adults fare worse (i.e., fluid intelligence) and one in which they fare better (i.e., crystallized intelligence). Specifically, we hypothesized that older adults' higher levels of crystallized intelligence can provide an alternate pathway to good decisions when the fluid intelligence pathway declines. The performance of older adults relative to younger adults therefore depends on the relative importance of each type of intelligence for the decision at hand. We tested this *complementary capabilities* hypothesis in a broad sample of younger and older adults, collecting a battery of standard cognitive measures and measures of economically important decision-making "traits"—including temporal discounting, loss aversion, financial literacy, and debt literacy. We found that older participants performed as well as or better than younger participants on these four decision-making measures. Structural equation modeling verified our hypothesis: Older participants' greater crystallized intelligence offset their lower levels of fluid intelligence for temporal discounting, financial literacy, and debt literacy, but not for loss aversion. These results have important implications for public policy and for the design of effective decision environments for older adults.

Keywords: Cognitive Aging; Decision Making; Fluid Intelligence; Crystallized Intelligence

Complementary Cognitive Capabilities, Economic Decision-Making, and Aging

1. INTRODUCTION

Lay people simultaneously hold two conflicting views about aging: that age brings wisdom, and that age brings diminished cognitive acumen. The idea that "older is wiser" has some empirical support: Older adults show better emotion regulation (Charles & Carstensen, 2010; Samanez-Larkin & Carstensen, 2011), better reasoning about interpersonal and intergroup conflicts (Artistico, Cervone, & Pezzuti, 2003; Grossmann et al., 2010; Thornton & Dumke, 2005), and, most relevant for the current research, higher levels of *crystallized intelligence*—i.e., experience and accumulated knowledge—into their 60s, after which it plateaus (e.g., Li et al., 2004; Salthouse, 2004).

However, cognitive aging research has also shown that a wide range of cognitive capabilities categorized as *fluid intelligence*—i.e., the ability to generate, transform and manipulate information—decline with age (e.g., Salthouse, 2004, 2010; Schaie, 1993). Fluid intelligence seems critical for decision-making, and the average 60-year-old will have lost more than one standard deviation in fluid intelligence since his or her 20s. Given these changes, *do* people become better decision-makers as they age, or do they get worse? And if older adults make better decisions, *how* do they make up for their lower levels of fluid intelligence?

Research in this area has typically examined the impact of age on either cognitive capability *or* on decision-making. In this paper, we examine the relationship among these measures, assessing younger and older adults on several important components of economic decision-making and relate observed differences to differences in cognitive capabilities. We focus on decision-making *traits*—for which we demonstrate measurement reliability and stability—known to affect the quality of a wide range of important real-world economic decisions. Specifically, we posited that older adults' higher levels of crystallized intelligence may provide an alternate pathway to good decisions, and that this may partially or fully make up for their lower levels of fluid intelligence. This interplay, which we call the *complementary*

capabilities hypothesis (CCH for short), should hold for a wide variety of decisions in which both the processing of new information and past experience can contribute to forming a good decision.

2. COGNITIVE CAPABILITIES, AGE, AND DECISION-MAKING

Cognitive aging research has consistently found that fluid cognitive capabilities decline with age starting from early adulthood. These capabilities include processing speed and efficiency (Li et al., 2004; Lindenberger, Mayr, & Kliegl, 1993; Salthouse, 1991, 1994, 1996), working memory (McArdle, Ferrer-Caja, Hamagami, & Woodcock, 2002; Salthouse, 1992), attention, and problem solving (Craik & Salthouse, 2000). Declines in *fluid intelligence* especially impact complex or novel tasks that require more active processing (Zacks, Hasher, & Li, 2000) and raise the question of how older adults can cope in daily decision making.

The present study examines the possibility that older adults' greater pool of knowledge and life experience can help offset their lower levels of fluid intelligence in terms of making good decisions. The concept of *crystallized intelligence* reflects this stable repository of knowledge acquired through experiences, culture, and education (Carroll, 1993; Cattell, 1971, 1987). Studies have shown that crystallized intelligence increases with age into the 60s and remains largely preserved thereafter (Horn & Cattell, 1967; Li et al., 2004; Salthouse, 2004, 2006, 2010).

2.1 Age differences in decision performance

Although these opposing age differences in fluid and crystallized intelligence have been robustly documented, studies examining age differences in decision-making have found conflicting results. As one would expect with decreasing fluid cognitive capabilities, some aspects of decision-making have been found to worsen with age, including susceptibility to framing effects (Finucane, Mertz, Slovic, & Schmidt, 2005; Kim, Goldstein, Hasher, & Zacks, 2005), applying decision rules (Bruine de Bruin, Parker, & Fischhoff, 2007), making the optimal choice as the number of options increases (Besedes, Deck, Sarangi, & Shor, 2010), and being

overconfident (Crawford & Stankov, 1996) and risk averse across many domains (Dohmen et al., 2011).

However, other studies find no age differences in susceptibility to framing (Mayhorn, Fisk, & Whittle, 2002; Roennlund, Karlsson, Laggnaess, Larsson, & Lindstroem, 2005), performance on the Iowa Gambling Task (Damasio, 1994), or the endowment effect (Kovalchik, Camerer, Grether, Plott, & Allman, 2005). Still other studies find that older adults are better at decision-making, with more accurate evaluations of their own knowledge (Kovalchik et al., 2005), being less affected by sunk costs (Strough, Mehta, McFall, & Schuller, 2008), and better at avoiding the influence of irrelevant alternatives (Kim & Hasher, 2005; Tentori, Osherson, Hasher, & May, 2001). Finally, some studies report a curvilinear relationship between age and decision-making, with middle-aged adults being more patient (Read & Read, 2004) and making fewer financial mistakes (Agarwal, Driscoll, Gabaix, & Laibson, 2010) than either younger or older adults.

2.2 Relating age differences in cognitive processes to decision making

Given this mixed picture of age differences in decision making, recent research has shown an emerging interest in the relationship between cognitive capabilities and decision making (Agarwal & Mazumder, 2013; Del Missier, Mäntylä, & Bruine de Bruin, 2011; Dohmen, Falk, Huffman, & Sunde, 2010; Shamosh & Gray, 2008) and in relating age differences in decision-making to age differences in these cognitive capabilities (Bruine de Bruin, Parker, & Fischhoff, 2011; Hanoch, Wood, & Rice, 2007; Mata, Schooler, & Rieskamp, 2007; Mather, 2006; Peters, Hess, Vaestfjaell, & Auman, 2007).

Much of this work explains age differences in decision-making as a result of age-related changes in the relative contributions of implicit, automatic, and often affective processing and deliberative and controlled processing. As deliberative processes decline with age, implicit and automatic forms of knowledge, such as affect, become more important inputs into decisions (Mather, 2006; Peters, Finucane, MacGregor, & Slovic, 2000; Peters et al., 2007). Because older

adults are less able to control the impact of automatic processing, they might be more susceptible to decision-making biases and marketing manipulations using affective appeals (Hess, McGee, Woodburn, & Bolstad, 1998; Hess, Waters, & Bolstad, 2000; Jacoby, 1999).

On the other hand, relying on affective cues has also been shown to be useful in some decisions, like in the Iowa Gambling Task (Damasio, 1994), so it is possible that changing decision making processes can benefit older adults in certain domains. Indeed, relying on heuristics and affective cues can be efficient, for example when older adults rely on simpler search strategies and take less information into account before making decisions (Besedes et al., 2010; Mata & Nunes, 2010; Mata et al., 2007; Queen & Hess, 2010). In these cases, greater experience-based knowledge helps older adults make appropriate decisions without actively processing all the information.

Although researchers have theorized about these possible connections between changing cognitive processes and age differences in decision making, few decision-making researchers have empirically assessed cognitive capabilities (for exceptions, see Agarwal & Mazumder, 2013; Del Missier et al., 2011; Dohmen et al., 2010). Studies that do relate cognitive capability to decision making generally do not include a broad enough set of cognitive measures, and in particular, do not distinguish between fluid and crystallized intelligence. For example, Shamosh and Gray (2008) found a positive relationship between patience in temporal discounting and general intelligence. Other studies, gathered as part of large national panels, have found positive relationships between financial literacy and measures of fluid intelligence such as numeracy and number series tasks (Banks, O'Dea, & Oldfield, 2010; McArdle, Smith, & Willis, 2009; Smith, McArdle, & Willis, 2010), but did not include measures of crystallized intelligence.

2.3 Complementary cognitive capabilities and decision-making

Although prior research has generally not combined decision-making measures with measures of both fluid and crystallized intelligence, the combination of older adults' lower levels of fluid intelligence but higher levels of crystallized intelligence gives rise to the possibility that

both may contribute to the effect of age on decision performance. This interplay between two opposing age differences in cognitive capability forms the basis for the CCH.

We represent the CCH as a multiple-pathway model in Figure 1. As indicated by the positive paths on the right side of Figure 1, we hypothesize that both fluid and crystallized intelligence positively affect decision performance. However, because of opposing age trends in these two capabilities (indicated by positive and negative paths on the left of Figure 1), understanding the relationship between age and decision performance requires understanding both pathways to good decisions. Using a notation similar to that of standard mediation analysis, we refer to the multiplicative product of age relationships with fluid and crystallized intelligence and their relationships with decision-making as the *indirect effects* of age on decision-making ($a_i \times b_i$), and the remaining path as the *direct effect* (c') of age. The *total effect* (c) is the relationship between age and decision-making when not controlling for intelligence.

--------------Figure 1--------------

Figure 1 has several implications. First, because there are opposing age trends for fluid and crystallized intelligence, examining the effect of one in the absence of the other results in omitted variable bias, which could either overstate or understate the effect of the observed variable. Second, the relationship between age and a given decision will depend not only on the relationships of age with fluid and crystallized intelligence but also on the relative impact of crystallized and fluid intelligence on that decision. If crystallized intelligence is a more important determinant of decision performance than fluid intelligence, we might expect older people to perform better. The opposite would be true for domains where fluid intelligence plays the more important role.

Finally, Figure 1 suggests that relationships between age and decision-making may be masked by the opposing indirect effects of age via crystallized and fluid intelligence (Zhao, Lynch, & Chen, 2010). The total effect (c) of age may appear to be zero, but there may nonetheless be opposing indirect effects of age on decision-making via crystallized and fluid intelligence. In addition, even when c is zero, the direct effect of age on performance (c') can be

significant when controlling for negative indirect effects. Our model therefore suggests that only looking for overall age effects (c) may be misleading and instead proposes that exploration of age differences in performance must also look for the complementary indirect effects of fluid and crystallized intelligence.

Note that Figure 1 is not meant to suggest that crystallized intelligence increases as a response to the loss of fluid intelligence with age. Instead, we assume that crystallized intelligence increases independently as a function of acquiring experience. Figure 1 simply draws attention to the possibility that experience and knowledge can provide another pathway to good decision-making, one that allows for good performance even when lower levels of fluid intelligence make reasoning-based pathways less successful. Many decisions can be executed or "solved" via multiple pathways (Weber & Lindemann, 2007). For example, people can make intertemporal financial choices by calculating net present values; or they can rely on their experience with similar past intertemporal tradeoffs without making explicit calculations.

3. STUDY

3.1 Overview

To explore the potentially complex relationships between age, cognitive capabilities, and decision-making, we administered multiple measures of cognitive capability and decision-making in four waves of an online study to younger and older adults. We analyzed the data using a standard two-step structural equation modeling (SEM) approach, first building separate measurement models for the cognitive capabilities and decision-making traits, and then analyzing the two measurement models together as functions of age. Since any measure of cognitive capability or decision-making can only measure the underlying trait with error, SEM allows us to assess the common variance shared by different measures of each underlying trait, giving us greater reliability than is possible with single measures. Although the entire model is of interest, we focus this paper on the role of the cognitive capabilities in partitioning the age differences on decision performance.

To the best of our knowledge, our study is the first to combine multiple standard measures of both fluid and crystallized intelligence from the cognitive aging literature with multiple measures of each of a number of important decision-making traits from the decision-making literature and to show their relationships with age. In doing so, we extend the standard paradigm used by the cognitive aging literature to the decision-making domain. Collecting multiple measures allows us to explicitly model measurement error, something that most decision-making studies do not do, instead assuming perfectly reliable measures, which is rarely justified.

3.2 Selection of decision-making traits

We assessed decision performance on six different "traits" suggested in the literature: Temporal discounting, loss aversion, susceptibility to anchoring, resistance to framing, financial literacy, and debt literacy. Rather than offering real-world decisions, the measures for these traits were designed to uncover underlying individual differences that form the basis for a wide range of real-world decisions with important financial and health consequences, which we detail for each trait below. We also hoped to establish whether performance on these measures would reveal reliable individual differences across different versions of each and across time—i.e., whether observed differences in performance on each measure reflect reliably measurable and stable decision-making traits.

Temporal discounting is the degree to which people discount future gains and losses and has been found to be much higher than would be expected, given the cost of borrowing, for most people (for review, see Frederick, Loewenstein, & O'Donoghue, 2002). The extent to which people discount has been found to affect saving decisions and the allocation of assets (Angeletos, Laibson, Repetto, Tobacman, & Weinberg, 2001), borrowing with credit cards (Meier & Sprenger, 2010), walking away from underwater mortgages (Atlas, Johnson, & Payne, 2011), smoking and other addictive behavior (Bickel & Marsch, 2001; Khwaja, Silverman, & Sloan, 2007), and lifestyle choices related to obesity and exercise (Chabris, Laibson, Morris, Schuldt, &

Taubinsky, 2008; Weller, Cook, Avsar, & Cox, 2008).

Loss aversion is the degree to which valuations of losses outweigh those of gains of the same magnitude (for review, see Tversky & Kahneman, 1991). Loss aversion has been shown to lead investment bankers to focus on avoiding losses rather than making gains (Willman, Fenton-O'Creevy, Nicholson, & Soane, 2002), small investors to hold onto losing stocks too long (Odean, 1998), home owners to set higher selling prices (Genesove & Mayer, 2001), and consumers to response asymmetrically to price changes (Hardie, Johnson, & Fader, 1993).

Financial literacy and debt literacy refer to the ability to understand financial information and decisions (Lusardi & Mitchell, 2007), and the ability to make decisions regarding debt contracts and understand interest rates (Lusardi & Tufano, 2009), respectively. Financial and debt literacy are increasingly important as consumers are faced with more difficult economic decisions. For retirement savings as an example, the increase in self-managed defined-contribution plans (e.g., 401K) presents challenges and opportunities not present in previous defined-benefit plans (e.g., pensions). People with greater financial literacy are more likely to accumulate and manage wealth effectively (Hilgert, Hogarth, & Beverly, 2003), plan for retirement (Lusardi & Mitchell, 2006, 2007, 2009), choose mutual funds with lower fees (Hastings & Tejeda-Ashton, 2008), and invest in the stock market at all (Van Rooij, Lusardi, & Alessie, 2011), whereas people with better debt literacy tend to avoid high-cost borrowing (e.g., payday loans), avoid incurring banking fees, and are more likely to transact in low-cost ways (Lusardi & Tufano, 2009). Many of these results hold internationally as well (Lusardi & Mitchell, 2011). Although financial and debt literacy questions do not seem like decision-making traits, they are just as important *determinants* of real-world decisions as our loss aversion and temporal discounting measures. In all cases, we are not interested in the answers or decisions *per se*, but in what the answers or decisions imply about the underlying decision traits.[1]

---

[1] A recent meta-analysis by Fernandes, Lynch and Netemeyer (2012) examined 103 studies with 390,071 respondents and found that measured financial literacy had a much higher correlation across the set of outcomes than manipulated literacy, suggesting that financial literacy may be the better conceptualized as a trait rather than an easily acquired form of knowledge.

Susceptibility to *Anchoring* is the tendency for consideration of one perhaps uninformative number to influence subsequent numerical judgments (for review, see Chapman & Johnson, 2002) and has been shown to affect consumers' perception of product values and purchase quantities (Ariely, Loewenstein, & Prelec, 2003; Nunes & Boatwright, 2004; Wansink, Kent, & Hoch, 1998), judgments of buying and selling prices (Simonson & Drolet, 2004), and credit card repayment amounts (Stewart, 2009).

Resistance to framing. Following Bruine de Bruin and colleagues (2007), we also attempted to measure people's tendency to be affected by normatively irrelevant variation in how problems are presented, e.g., whether options are framed as gains versus losses (Tversky & Kahneman, 1981). Option framing has been shown to affect decisions regarding alternative cancer treatments (McNeil, Pauker, Sox, & Tversky, 1982), insurance (Johnson, Hershey, Meszaros, & Kunreuther, 1993), and health behaviors (Rothman & Salovey, 1997).

3.3 Methods

3.3.1 Sample and Procedure

Younger adults (age range: 18-29, $M = 24.76$, *Median = 25*, $SD = 2.91$) and older adults (age range: 60-82, $M = 66.39$, *Median = 65*, $SD = 4.93$) from the Columbia University Center for Decision Sciences' Virtual Lab Panel completed all four waves of a web-based survey consisting of cognitive, decision-making, and demographic measures.[2] This panel consists of 55,000 people who have agreed to participate in psychological and decision research for financial compensation. We selected participants from the panel who fell within each specified age range and were U.S. residents. Participants received email invitations between February and June 2009 (waves 1-3) and between June and September 2010 (wave 4). Delaying the last wave by a year provided a strong test of the reliability of the decision measures and the stability of the underlying traits. Only participants who completed each wave received invitations to subsequent

---

[2] We used an extreme group design to maximize our ability to detect age differences, but acknowledge the desirability of a middle-age group, especially in terms of exploring curvilinear trends. However, note that we found no differences in analyses whether we treated age as a binary or continuous variable, and adding a quadratic age term does not improve model fits.

waves. Participants were paid $25 upon completion of the first three waves and $15 for the fourth via their choice of PayPal payments or Amazon.com gift certificates. In addition, three of the decision-making measures were incentive-compatible.[3]

------------------Table 1------------------

In total, 632 American participants ($N_{young} = 332$, $N_{old} = 300$) completed the first wave, 562 (11.1% dropout) completed the second, 516 (8.2% dropout) completed the third, and 336 (34.9% dropout) completed the fourth, for a total dropout rate of 46.8%. The dropout rates were low considering that more than a year elapsed between the first and fourth waves (Reips, 2002). Importantly, there was no difference in dropout between younger (47.9%) and older groups (45.7%). No demographic, cognitive, or decision-making measure predicted whether participants dropped out, suggesting that we do not need to account for selective attrition.[4]

Our final sample consisted of 173 younger and 163 older participants. Table 1 shows the socioeconomic distributions by age group. Older participants were somewhat more educated than younger participants, with a higher percentage attaining post-graduate degrees (26.4% vs. 15.0%, $\chi^2(1) = 6.63$, $p < .01$) and more years of education on average (15.4 vs. 14.8, $t = 2.30$, $p < .05$). However, they similar levels of household income (medians, $Med_{old} = \$58.6K$ and $Med_{young} = \$61.1K$, $t = .58$, ns), somewhat higher than the U.S. median of $49,445 in 2010 (U.S. Census). Household income was positively correlated with years of education ($r = .22$, $p < .0001$).

3.4 Description of Measures

Next, we briefly describe all measures used in our study. More details can be found in the Supporting Online Materials.

3.4.1 Cognitive measures

Table 2 lists the eight standard cognitive measures of fluid and crystallized intelligence.

---

[3] Intertemporal choices in the first, third, and fourth waves were played for real money for 1 in 50 participants. These additional payments ranged from $20 to $110 depending on participants' choices.
[4] The only exception is that males dropped out at a higher rate (15.2%) after the first wave than females (9.0%; $\chi^2(1) = 5.38$, $p = .02$). However, this gender difference reversed for the remaining waves, with no difference in overall dropout rates (45.5% for males vs. 47.5% for females; $\chi^2(1) = 0.22$, ns).

These measures were distributed across all four waves and interspersed with the decision-making measures and each other. Details on all measures can be found in the supporting online materials.

Fluid intelligence. Among our measures of fluid intelligence, the most widely used is *Raven's Progressive Matrices*, a non-verbal test of inductive and analytic reasoning. Our version asked participants to determine which option correctly filled in the missing cell for each of 18 3×3 matrices (Salthouse, Pink, & Tucker-Drop, 2008). We also included two other standard measures of inductive and reasoning ability: *Letter Sets* (Salthouse et al., 2008) asked participants which of five letter sets (e.g., NOPQ, DEFL, ABCD, HIJK, and UVWX) did not fit the rule that the other four fit (e.g., DEFL). *Number Series* asked participants to fill in the blank in six series of numbers (e.g., 23, 26, 30, 35, __ ; correct answer is 41) in an adaptive two-block version developed by McArdle and Woodcock (2009).

------------------Table 2------------------

Finally, we also included, for comparison, two less standard tasks commonly used in decision research as proxies for fluid intelligence: The *Cognitive Reflection Test* (CRT; Frederick, 2005; Frederick et al., 2002) consists of three math questions that yield quick but incorrect first responses, and *Numeracy* (Lipkus, Samsa, & Rimer, 2001) tests understanding of probability and mathematical concepts. Although these measures positively correlate with the other fluid intelligence measures, we omitted these more math-focused tasks from the final cognitive measurement model to maintain the generality of the fluid intelligence factor.

Crystallized intelligence. We included three crystallized intelligence measures. *Shipley Vocabulary* is a 40-item multiple-choice synonym vocabulary test, and our version was adapted from CREATE's Common Core Battery of Measures (Czaja, Charness, Dijkstra, et al., 2006; Czaja, Charness, Fisk, et al., 2006). Similarly, *Antonym Vocabulary* (Salthouse, 1993) measured vocabulary using 10 multiple-choice antonym selection items. Finally, WAIS-III *Information* (Wechsler, 1997), as adapted by CREATE (Czaja, Charness, Dijkstra, et al., 2006; Czaja, Charness, Fisk, et al., 2006), asked participants 28 open-ended general-knowledge questions about events, objects, places, and people.

3.4.2 Decision measures

We included three to five measures of each decision-making trait, again distributed across all four waves (see Table 2) and interspersed with other measures. Different measures of the same trait were presented in fully counterbalanced order within each wave to control for order effects. Since no order or item effects were found for any decision-making measure, we will not discuss them any further. Importantly, performance on each measure can be classified by the degree to which it conforms to normative economic models, as described below.

Temporal discounting was measured with five choice titrators (Green, Fry, & Myerson, 1994). Three of the titrators presented participants with a series of choices between a fixed smaller gift certificate today ($60, $55, and $100) and varying amounts of a larger gift certificate at a delayed time point (4, 3, and 12 months). The remaining titrators instead fixed the larger, future gift certificate ($75 and $115 in 3 months) and varied the amount of a smaller gift certificate today. The dependent variable for each titrator was the participant's exponential annual discount factor (which can theoretically range from 0 to 1) as implied by the midpoint between preferring the earlier versus later payments (i.e., the indifference point). Using hyperbolic discounting rates gives similar results. Because nearly all participants revealed impatience levels that appeared too high relative to the economic standard (i.e., the interest rate on available loans and credit cards), larger discount factors (closer to one), indicating more patient preferences, were coded as better.

Loss aversion was also measured with five choice titrators. Each titrator presented participants with a series of choices indicating willingness to play each of a series of binary gambles with a 50% chance of winning some fixed amount ($6 or $20) and a 50% chance of losing some varying amount (between $0.50 to $7 in $0.50 increments or between $2 to $24 in $2 increments). Two of the titrators in the first wave were repeated in the fourth wave 1 year later without any change. We calculated loss aversion coefficients by dividing the gain amount by the loss amount at the indifference point (i.e., midpoint between where the participant switches from willing to play the gamble to not willing). Because a loss aversion coefficient of 1

is economically normative and 93.2% of responses yielded loss aversion coefficients greater than 1, coefficients were reverse-coded so that larger values were better.

Financial literacy was measured using three widely used financial literacy questions (Lusardi & Mitchell, 2006) designed to assess knowledge of fundamental economic concepts, and *debt literacy* was measured using three debt literacy questions (Lusardi & Tufano, 2009) designed to assess knowledge of compound interest and credit card debt. Answers were simply coded as correct or not.

Anchoring was measured with two sets of three numerical estimation questions each, with low, high, or no anchors. Higher z-scores, corresponding to being less susceptible to anchoring, were coded as better. *Resistance to framing* was measured with four variants of the Asian disease problem, each offering a choice between a risky option and a sure option, while varying the framing of the options as gains or losses (Tversky & Kahneman, 1981). Resistance to framing was determined by whether choices for the pair of gain and loss scenarios in each wave were consistent—that is, both risk-seeking or both risk-averse.

4 RESULTS

4.1 Preliminary Analysis

We cleaned the data set using preplanned, standard procedures, removing non-monotonic responses from the temporal discounting (1.2%) and loss aversion (1.9%) titrators, since they represent participants who did not understand or attend to those measures. There were no age differences in the proportion of non-monotonic titrator responses. We also removed exactly correct answers for the anchoring questions (4.3%), since anchors have no chance of affecting people who actually know the correct answers.[5] We then log-transformed all skewed variables ($|skew| > .8$), standardized all variables, and removed outliers beyond 3.5 standard deviations (7 data points in total). Importantly, we coded all variables so that higher scores corresponded to

---

[5] A substantial number of participants knew how many bones were in the adult human body (11.9%) and the year Beethoven was born (5.7%). Younger participants gave more correct answers (6.1%) than older participants (2.5%). Including these exact answers does not substantially impact results.

better performance.

4.2 Overview

We followed procedures standard to the cognitive aging literature (e.g., Del Missier et al., 2011; Lindenberger et al., 1993; Salthouse, Atkinson, & Berish, 2003) for analyzing the relationships between age, cognitive capability, and other abilities. We first characterize the cognitive measurement model by testing for convergent and discriminant validity, and showing measurement invariance between younger and older groups. We do the same for the decision-making variables. Finally, we combine these models with age in a structural equation model to test the CCH. We ran all analyses in Mplus (Muthén & Muthén, 2010) using both standard and bootstrapped estimation procedures using 10,000 bootstrapped samples (Preacher & Hayes, 2008; Shrout & Bolger, 2002). We report the results for standard analyses but, for all tests, the significance levels for bootstrapped analyses (corresponding to the widest bias-corrected confidence interval not including zero) were equally or even more significant.

We used standard indices to evaluate model fit. Root mean square error of approximation (RMSEA) is a measure of the difference between predicted and observed covariances, with values under .08 considered adequate (Browne & Cudeck, 1993; Steiger, 1990). The Bentler comparative fit index (CFI) indicates the relative improvement of the hypothesized model over the null or independent model (in which all variables are unrelated). Values of CFI above .90 are considered adequate (Hu & Bentler, 1999). Both indices are penalized for model complexity and therefore favor models that can more parsimoniously explain the observed covariance patterns. We also report difference in chi-squares for model comparisons but do not interpret overall chi-square due to our large sample size (Kline, 2010).

4.3 Cognitive measurement model

------------------Table 3------------------

Table 3 shows the mean and variance for each cognitive measure for younger and older participants, as well as the pairwise correlations between the measures across both age groups.

Different measures for each cognitive factor were significantly correlated with one another (rs = .23 to .53 for fluid intelligence, and .51 to .63 for crystallized intelligence; all ps < .0001). To determine the validity of the cognitive measurement model, we conducted a confirmatory factor analysis (CFA) on the cognitive measures. As seen in the factor loadings in Figure 2, the two-factor model consisting of fluid intelligence (G_f) and crystallized intelligence (G_c) factors showed convergent validity, with significant loadings for all cognitive measures on their hypothesized factors. The model showed reasonable fit to the data (CFI = .94, RMSEA = .079). Fluid intelligence was positively correlated with crystallized intelligence (r = .31, p < .0001).

We also fit two standard comparison models: a single-factor model, and a two-factor model in which the factors are forced to be uncorrelated. Both alternative models fit the data significantly less well than the hypothesized two-factor model with correlated factors (χ^2 difference tests, $\chi^2(1)$ = 19.00 and 138.58, respectively, both p < .00001). Therefore, despite significant inter-factor correlation, the hypothesized measurement model demonstrates discriminant validity.

------------------Figure 2------------------

4.3.1 Measurement invariance

We first examine whether the cognitive measures assess the same underlying factors in the same ways in each age group, by testing for measurement invariance (Kline, 2010; Vandenberg & Lance, 2000). We tested for factor invariance using multiple-group CFA, which separately fits the measurement model simultaneously to the data from the younger and older groups. Table 4 shows the fit indices for successively more restrictive models. Model M1 specifies the same measurement model for both age groups with all parameters freely estimated within each group. M1 fit the data well (CFI = .972, RMSEA = .069), suggesting that the measurement model satisfies configural invariance (Kline, 2010).

With the exception of Raven's Progressive Matrices, our proposed factor structure demonstrated strong metric invariance. Model M2, which restricts the factor loadings to be equal across age groups for each cognitive measures, did not fit the data as well as M1 ($\Delta\chi^2(4)$ = 12.09,

$p < .05$). This discrepancy appeared to be due to a difference in the loading of Raven's Progressive Matrices. An alternative model M2', with equal factor loadings except for Raven's, did not fit the data significantly differently from model M1 ($\Delta\chi^2(3) = 6.18$, *ns*). Similarly, model M3, in which factor intercepts were restricted to be equal across age groups, fit worse than M2' ($\Delta\chi2(4) = 28.13$, $p < .0001$), whereas alternative model M3', with equal factor intercepts except for on Raven's, fit about the same as M2' ($\Delta\chi^2(3) = 4.53$, *ns*). These results suggest that the measurement properties of Raven's Progressive Matrices were different between younger and older groups. However, relaxing this restriction did not change the results of subsequent analyses, so we continue under the assumption of partial strong metric invariance for the cognitive measurement model.

Finally, model M4, in which factor variances and covariances were restricted to be equal across age groups, fit about as well as model M3' ($\Delta\chi^2(3) = 2.23$, *ns*), suggesting that the factor variances and covariances were equivalent across age groups.

------------------Table 4------------------

4.3.2 Age differences for cognitive factors

Having established measurement invariance between the younger and older groups, we can now test for age differences. Table 3 shows that younger participants were significantly better on all fluid intelligence measures (all ts > 11, all ps < .0001) but significantly worse on all crystallized intelligence measures (all ts > 3.78, all ps < .001). The same differences manifested at the factor level when we added paths to age in the measurement model. Relative to younger participants, older participants had significantly lower fluid intelligence ($\beta = -.50$, $p < .0001$) but significantly higher crystallized intelligence ($\beta = .47$, $p < .0001$). The similar magnitudes but opposite directions of these age differences are a necessary condition for the CCH.

4.4 Decision traits measurement model

The lower half of Table 3 shows the mean scores for each decision measure for each age group, as well as the correlations between these measures and the cognitive measures. Different

measures of temporal discounting (rs = .33 to .62, all ps < .0001), loss aversion (rs = .41 to .82, all ps < .0001), financial literacy (Spearman rs = .07 to .40, all ps < .001, except for correlations with the third question), and debt literacy (Spearman rs = .15 to .33, all ps < .01) were significantly correlated with one another. However, different measures for resistance to framing (r = -.05, ns) and anchoring (rs = 0 to .15, two ps < .05 and others ns) were not significantly correlated, suggesting that neither set of measures reliably assessed their underlying decision-making traits. We thus omitted anchoring and framing in all subsequent analyses.

We next conducted a CFA on the remaining, reliable decision-making measures for temporal discounting, loss aversion, financial literacy, and debt literacy. As seen in the factor loadings in Figure 3, all four decision-making factors showed convergent validity. The four-factor model showed good fit (CFI = .948, RMSEA = .038).[6] There were correlations between some of the decision-making factors, of temporal discounting with loss aversion (r =.12, $p <$ .10), financial literacy (r =.41, $p <$ .001), and debt literacy (r =.39, $p <$ .001), and of debt literacy with loss aversion (r =.25, $p <$ .01) and financial literacy, (r =.75, $p <$ .001).[7]

------------------Figure 3------------------

4.4.1 Measurement invariance

As with the cognitive measurement model, we tested whether the decision-making measures assessed the same underlying factors for younger and older participants using multiple-group CFA. Table 5 shows model fits and difference tests for each step of this procedure. Models DM1, DM2, and DM3 showed that the decision-making factors satisfy configural invariance, weak metric invariance, and strong metric invariance, respectively. Model DM4, which fixed factor variance and covariance to be equal across groups fit significantly worse than DM3

---

[6] The decision-making factor model allows residual correlations between the first discounting measure and the second and third temporal discounting measures, and between the first and second loss aversion measures. Each pair of measures used nearly identical methods so it is reasonable that they share unexplained variance. Again, omitting these residual correlations affects model fit but not subsequent results.

[7] The correlation between financial and debt literacy (r =.75, $p <$ .001) raised concerns of potential multicollinearity. However, when we compared the four-factor model with a three-factor model in which financial and debt literacy were combined into a single factor, model fits were significantly worse (RMSEA = .041, CFI = .938), $\chi^2(3)$ = 9.42, p = .02.

($\Delta\chi^2(10) = 19.30$, $p < .05$) but this was due to the financial literacy factor having much higher variance for the young group (.80) than the old group (.11). Model DM4' showed that factor variances and covariances were equal across age groups for all decision-making factors except for the variance of financial literacy. In short, the decision-making measures assessed the same underlying decision-making traits for younger and older groups, with the minor exception that financial literacy was more varied among younger participants.

------------------Table 5------------------

4.4.2 Age differences for decision-making factors

Table 3 also shows that older participants generally tended to make better decisions. Older participants were significantly more accurate on the financial and debt literacy questions and somewhat more patient on the temporal discounting questions. We tested these age differences on the factor level by adding paths to age: Relative to younger participants, older participants were significantly more financially literate ($\beta = .47$, $p < .0001$) and debt literate ($\beta = .24$, $p < .01$), marginally more patient at temporal discounting ($\beta = .12$, $p < .10$), but equally loss averse ($\beta = .09$, *ns*). However, before concluding that our older participants are generally better decision-makers than our younger participants, we note that these main effects of age do not directly address the CCH, which we more directly test below.

4.5 Relationships between cognitive capabilities, decision performance, and age

Having established convergent and divergent validity and reasonable measurement invariance for both the cognitive capabilities and decision performance factors, we now examine the relationships between these factors and age. First, we explored simple relationships between cognitive capabilities and decision performance by combining the cognitive and decision-making models and adding paths between all decision-making factors to all cognitive factors in a structural equation model (SEM). SEMs combine path analysis with factor analysis, concurrently estimating four multiple regressions of the decision-making factors on the cognitive capabilities while simultaneously estimating the factor structures for all cognitive and decision-making

measures.

Table 6 shows the standardized coefficients of all SEM model paths. Temporal discounting, financial literacy, and debt literacy were all positively related to both fluid and crystallized intelligence, as predicted, but loss aversion was related to neither. In this and all subsequent SEM analyses, we included demographic controls for gender, education, and income to try and remove possible confounding effects due to underlying demographic differences between the younger and older groups (such as older participants being more educated). Models without demographic controls were nearly identical, with a slightly more significant effect of age on temporal discounting ($\beta = .11$, $p < .10$).

-----------------Table 6------------------

4.5.1 Multiple pathway analysis

In the final analysis step, we used the approach outlined in Figure 1 to test whether age differences in the cognitive capabilities can help explain the observed age differences in decision performance. Importantly, we were able to simultaneously estimate and test all direct and indirect effects within a single SEM framework. Doing so allows us to estimate indirect effects of age even if the total effect of age on a given factor is not significant (Zhao et al., 2010). That is, age differences in cognitive capabilities may partially explain decision performance in young and old participants, even if we observe no main effect of age.

Recall that Figure 1 represents the CCH as a path model. In the language of this model, the CCH predicts that any age differences in decision-making are partially due to opposing indirect effects of age via fluid and crystallized intelligence, where older participants' lower levels of fluid intelligence may be offset by their higher levels of crystallized intelligence. In other words, older participants' higher levels of crystallized intelligence may provide an alternate pathway to good decision-making, which may make up for the decrement in the fluid intelligence pathway.

Table 7 shows the standardized coefficients of the relevant paths in the final SEM model, which adds paths from age to fluid and crystallized intelligence to the model in Table 6. This

multiple pathway model fits the data reasonably well (CFI = .90, RMSEA = .042). Recall that the total effect of age (*c* in Figure 1) for a given decision trait is equivalent to the path from age to the decision-making factor in a model without fluid and crystallized intelligence. The significance of an indirect effect of age tests whether that cognitive capability contributes to the effect of age on that decision-making factor. The direct effect of age (*c'*) is the path from age to the decision-making factor after all indirect effects have been accounted for in the model.

------------------Table 7------------------

In Table 7, CCH would be confirmed by fluid and crystallized intelligence having negative and positive *indirect* effects on decision-making, respectively. This pattern, and in particular the similar magnitudes and opposite directions of the indirect effects, is evident for three of the four decision-making factors. Looking, for example, at temporal discounting, both fluid and crystallized intelligence positively contributed to patient discounting, but have opposing *indirect* effects—due to opposing changes with age—that perfectly offset each other. That is, older participants' higher levels of crystallized intelligence provided another pathway to patient intertemporal choices, preventing them from making the more impatient choices that their lower levels of fluid intelligence would otherwise predict.

Similar results hold for financial literacy and debt literacy. Older participants' higher levels of crystallized intelligence offset their lower levels of fluid intelligence, fully for financial literacy and mostly for debt literacy. Because fluid intelligence is more important than crystallized intelligence for debt literacy (a×b$_{Gf}$ = -.31 vs. a×b$_{Gc}$ = .23, *p*s < .001), the net of the indirect effects of fluid and crystallized intelligence is slightly negative (-.08, *ns*), although not significantly so. In other words, older participants would have an even larger advantage over younger participants in debt literacy if they had the younger participants' levels of fluid intelligence.

Finally, as anticipated by the simple SEM results, we found that complementary capabilities did not explain age relationships with loss aversion. We comment further on this lack of support below.

4.6 Alternative Analysis

A number of recent papers have documented issues in interpreting the results of cross-sectional studies of age-based mediation effects (Lindenberger & Pötter, 1998; Lindenberger, von Oertzen, Ghisletta, & Hertzog, 2011; Maxwell & Cole, 2007). In particular, cross-sectional mediation effects are strongly influenced by the age-independent relations between the mediators and dependent variables. Although our hypothesis is not meant to generalize the cross-sectional finding to a longitudinal causal effect, it is nonetheless possible that the model estimates presented above are biased due to these issues.

Since the CCH hypothesis is simply about different levels of cognitive capabilities in different age groups and not about changes in these capabilities over time, we now present an alternate set of analyses using a technique introduced by Schmiedek and Li (2004; hereafter S&L). The S&L analyses are meant as a complement to the standard mediation analyses already presented, and are intended to show the robustness of our results to these issues with cross-sectional mediation analysis. These alternative analyses provide necessary convergent evidence for our theoretical story, and are the analysis of choice for life-span research. However, we chose to retain the more familiar mediational framework above as a more accessible guide to those who are less familiar with the nuances of structural equation modeling.

Specifically, the S&L reformulation of our model partitions the variance for each decision-making variable into variance explained by fluid and crystallized intelligence, and variance explained by that specific decision-making component. The key difference is that rather than having decision-making indicator measures load only on their respective decision-making factors, each decision-making measure loads on the specific decision-making factor *and* the two cognitive factors. As before, the cognitive variables still only load on their respective cognitive factors. Age is then added to this model as a covariate. One possible outcome of these analyses, consistent with the CCH, would be that decision variables have significant positive loadings on the cognitive factors, while fluid intelligence correlates negatively and crystallized intelligence correlates positively with age. This result would suggest that age differences in decision making

can only be understood if the opposing effects of fluid intelligence and crystallized intelligence are taken into account.

The S&L reformulation of the model fits reasonably well (CFI = .91, RMSEA = .043). Table 8 reports the factor loadings and correlations with age for the S&L analysis. All variables loaded significantly on their specific factors. In addition, all debt literacy measures and most temporal discounting and financial literacy measures loaded on fluid intelligence; and all temporal discounting, financial literacy, and debt literacy measures except one loaded significantly on crystallized intelligence. The loss aversion measures did not load on either cognitive factor. The fluid and crystallized intelligence factors were positive correlated ($r = 0.39$, $p < .001$). These results suggest that individual differences in temporal discounting, financial literacy, and debt literacy—but not loss aversion—are partially explained by individual differences in fluid and crystallized intelligence.

In addition, controlling for the decreasing relationship between fluid intelligence and age and the increasing relationship between crystallized intelligence and age, the remaining variance in temporal discounting, loss aversion, and financial literacy were all unrelated to age, whereas the remaining variance in debt literacy was positively correlated with age. These results suggest that age differences in fluid and crystallized intelligence fully explain any age differences in temporal discounting, loss aversion, and financial literacy, but only partially explain age differences in debt literacy. These results are largely consistent with the results of the standard cross-sectional mediation analyses in Section 4.5, and provide convergent support for the CCH.

4.7 Summary of results

In sum, our older participants performed as well as or better than younger participants on all decision-making measures. We found that fluid intelligence and crystallized intelligence partially explained the effect of age on performance for four stable, trait-like decision-making traits. In particular, we found support for the hypothesized complementary effects of fluid and crystallized intelligence on temporal discounting, financial literacy, and debt literacy across age

groups: Older participants' higher levels of crystallized intelligence offset their lower levels of fluid intelligence. However, for financial literacy, the direct effects of age remained, and for debt literacy, they were magnified after controlling for fluid and crystallized intelligence. These residual age effects suggest that there is some component of these traits not captured by our cognitive measures, possibly along the lines of domain-specific knowledge or expertise. We discuss this further below.

5. DISCUSSION

The average age of the world's population is rising rapidly, and the proportion of people older than 60 years will continue growing until at least 2050 (United Nations, 2002). Understanding how and how well older adults make decisions is crucial because they are faced with an increasing number of important choices related to their retirement finances and health care (Mather, 2006; Peters et al., 2000; Peters et al., 2007; United Nations, 2002). Furthermore, as new laws increase the minimum retirement age, people remain professionally active later in life, with older adults holding many key leadership roles. Given their influence over the economy and society, this paper set out to explore whether older adults are better or worse decision-makers than younger adults, and why. We hypothesized that any age differences in decision performance would be related to the complementary contributions of fluid and crystallized intelligence to the specific decision.

The opposing age differences for fluid and crystallized intelligence, together with their positive relationships with decision performance, provided the underpinnings for our complementary capabilities hypothesis of how age differences in cognitive capabilities help explain age differences in decision performance, which was supported for temporal discounting, financial literacy, and debt literacy. For these decision traits, lower levels of fluid intelligence in older adults were related to lower decision performance, but higher levels of crystallized intelligence offset this negative age effect to some degree. For temporal discounting and financial literacy, crystallized intelligence perfectly offset differences in fluid intelligence,

leading to no net age effect. On the other hand, higher levels of crystallized intelligence were not enough to fully offset lower levels of fluid intelligence for debt literacy, where the pathway through fluid intelligence was more important than the pathway through crystallized intelligence.

5.1 Age differences in decision performance

Our older participants showed equal or better decision performance than our younger participants, exhibiting greater patience in temporal discounting and better financial and debt literacy. Our results on temporal discounting are in line with other studies showing that older adults are more patient (Green et al., 1994; Reimers, Maylor, Stewart, & Chater, 2009). However, other research has found that found that older participants (mean age of 80) were less patient than younger participants (Trostel & Taylor, 2001), or that patience increases into the 50s before dropping in the 70s (Read & Read, 2004; Souzou & Seymour, 2003). These discrepancies may be due to the average age of the older group in each study. For instance, Green and colleagues' (1994) older group was close in age to their middle-aged group, and Reimers and colleagues (2009) did not have meaningful data for people above 65. This argument also holds for the current study, in which the mean age for older participants was 66. This reinforces the point that the distribution and mean ages of older respondents will be critically important in making predictions about the effects of age as will factors that determine the life course of fluid and crystallized intelligence such as education and health.

Our finding that older participants were better at financial and debt literacy are consistent with research by Delavande and colleagues (2008). However, other research has found a negative relationship between debt literacy and age (Lusardi & Tufano, 2009) and an inverted U-shape relationship between financial literacy and age (Lusardi & Mitchell, 2011). These conflicting results are most likely due to differences between samples, and as we describe below, the underlying CCH can explain these ostensibly contradictory results as well.

Finally, we found that older participants were somewhat less loss averse, although this result did not reach standard levels of significance. The lack of age differences for loss aversion

are consistent with studies showing no age-related differences in tasks that are posited to depend on loss aversion such as the Iowa gambling task (Kovalchik et al., 2005; MacPherson, Phillips, & Della Sala, 2002; Wood, Busemeyer, Koling, Cox, & Davis, 2005), framing effects (Mayhorn et al., 2002; Roennlund et al., 2005), and the endowment effect (Kovalchik et al., 2005). Despite the empirical consistency, we nonetheless caution that our result is preliminary and may be due to limitations of the loss aversion titrators we used to measure the trait. On the one hand, these five measures share enough variance to reliably measure loss aversion; but they may not fully capture the essence of a trait as complex as loss aversion. Future research should consider a broader range of loss aversion measures.

5.2 Decision performance across the life span

Although we have reported numerous contradictory findings relating age to decision performance, CCH suggests one way of reconciling these data by positing two pathways to good decision performance. Our study, which omitted participants aged 30 to 59 (to increase the power of our analyses) and has few participants older than 80, does not allow us to directly trace decision performance across the entire life span. However, a large body of past research *has* examined differences in cognitive capabilities across the life span and we can make rough extrapolations to the unstudied age ranges if we assume—supported by our data—that the roles of fluid and crystallized intelligence remain constant across the life span.

For example, research has found that crystallized intelligence tends to plateau while fluid intelligence is even lower for adults aged 70 and above (Li et al., 2004; Salthouse, 2004, 2010). The CCH therefore suggests that the relationship between age and decision performance will be characterized by a single-peaked function. Figure 4 presents an approximate picture, using our estimated relationships between age, cognitive capabilities, and decision performance, and extrapolating to other ages using Salthouse's (2004) assessments of the levels of fluid and crystallized intelligence. Figure 4 also does not take into account a) the standard errors of the estimated trajectories in Salthouse (2004), b) the standard errors of the regression weights, or c) potential age differences in the regression weights. Although the exact nature of this function

(e.g., the location of the peak) will depend on these parameters and the relative importance of crystallized and fluid intelligence to the domain, an inverse-U-shaped relationship with age is evident for all three decision traits for which we found age differences. This shape is consistent with the age patterns other research have found for temporal discounting (Read & Read, 2004), career productivity (Simonton, 1997), and financial decision-making (Agarwal et al., 2010).

------------------Figure 4------------------

5.3 How does crystallized intelligence offset age-related declines?

Although our results indicate that crystallized intelligence helps older adults offset their lower levels of fluid intelligence, our measures of crystallized intelligence may not be the whole story. Recall that we followed standard practice in assessing crystallized intelligence using two measures of vocabulary and one of general knowledge (e.g., Friedman et al., 2006; Hambrick, Salthouse, & Meinz, 1999; Mata et al., 2007; Ratcliff, Thapar, & McKoon, 2010), rather than measuring domain-specific crystallized intelligence. How does knowing the definition of "corpulent" or the identity of Catherine the Great contribute to greater patience in intertemporal choice? Although knowledge of this sort may affect performance on linguistic tests or crossword puzzles (Hambrick et al., 1999), it seems unlikely that it directly affects temporal discounting or financial and debt literacy. However, vocabulary skill and general knowledge may be a *proxy* for domain-specific knowledge, experience, and expertise that can facilitate better and more forward-looking decision-making. Because it is difficult to assess domain-specific crystallized intelligence across many domains, it seems reasonable to use domain-general measures of crystallized intelligence as a stand-in when examining multiple domains. Given their generality, it is remarkable that these domain-general measures work as well as they do, and future research should follow the recent work of Ackerman and colleagues (e.g., Ackerman, 2007; Ackerman & Beier, 2006) to better understand and disentangle the effects of domain-general versus domain-specific crystallized intelligence.

Crystallized intelligence could also be correlated with a related, but unmeasured

construct. For example, Socioemotional Selectivity Theory (SST) posits that older adults, who perceive a limited time left in their life, try to optimize their experiences by maintaining positive emotions and by focusing their attention on positive information and stimuli (Carstensen, 2006; Carstensen, Isaacowitz, & Charles, 1999; Mather & Carstensen, 2005). For example, older adults prefer to seek positive and avoid negative stimuli (Isaacowitz, Allard, Murphy, & Schlangel, 2009) and have better memory for positive information (Charles, Mather, & Carstensen, 2003). Older adults may also adapt to declines in cognitive resources by becoming increasingly selective about how they expend their effort (Hess, 2000; Hess, Rosenberg, & Waters, 2001). Similarly, Dynamic Integration Theory (Labouvie-Vief, 2003) suggests that age-related differences in positivity bias arise because positive information is less resource demanding than negative information.

Mather (2006) argues that these differences in emotional processes may provide an explanation for why there are age differences for some types of decisions but not others. For example, positivity bias has been used to explain age-related differences in temporal discounting as well as decision-making tasks related to loss aversion (Carstensen, 2006; Carstensen et al., 1999; Mather & Carstensen, 2005). In related research, Samanez-Larkin and colleagues (2007) found no age differences in neural activation during gain anticipation but a relative reduction in activation for older adults during loss anticipation.

Although changes in positivity bias may be important for understanding decision-making across the lifespan, they present a challenge relative to more established constructs such as fluid and crystallized intelligence, as there exist no standard, domain-independent battery of measures to assess positivity bias. Again, we leave this as a topic for future research when more standardized measures are developed.

5.4 Extension to other decision measures

We set out to measure performance on a broad set of economically important decision-making traits and believe that it would be desirable to examine an even larger set of measures.

Other researchers have begun to explore the relationships between cognitive capabilities and some of these other decision variables, including risk taking (Dohmen et al., 2010; Henninger, Madden, & Huettel, 2010), retirement savings (Banks et al., 2010; McArdle et al., 2009), and correctly using credit cards and other sources of borrowing (Agarwal et al., 2010; Agarwal & Mazumder, 2013). However, most of these studies have collected only a small subset of cognitive capability measures, which limits how well they can establish the validity and reliability of their cognitive capabilities and hence the reliability of their relationships with decision performance. Of these studies, the one with the most cognitive measures (Henninger et al., 2010) examined the effects of processing speed and memory on risk aversion, but did not consider potential positive effects of cognitive capabilities in which older adults are better. It is impossible to study the effects of variables one does not measure, but these omitted variables may very well bias existing findings.

Two additional papers recently explored the relationships among age, cognitive capabilities, and general decision-making capabilities (DMC) as measured by the adult DMC scale (Bruine de Bruin et al., 2011; Del Missier et al., 2011). Bruine de Bruine and colleagues (2011) considered the effects of cognitive capabilities in which older adults are better, but did so without attempting to directly measure such capabilities. They instead used age as a proxy for any capabilities that increase with age, after partialling out the effect of fluid intelligence. However, this orthogonalization of the variables did not allow them to specifically identify a complementary role for crystallized intelligence. Del Missier and colleagues (2011) complemented these results by collecting measures for a different set of cognitive capabilities. They showed that three core executive functions affect different aspects of the DMC differently. Future research in this area would benefit from combining a broad set of cognitive capability measures, including multiple measures for fluid and crystallized intelligence, with an even broader set of decision-making traits.

Our use of multiple measures of each decision-making trait allowed us to assess reliability and increased the robustness of our results by using only the variance shared by all

measures of each decision-making trait. Our results indicate that some decision-making traits have substantial common variance and in the case of temporal discounting and loss aversion, substantial stability over 1 year (see also Meier & Sprenger, 2013). Further work should make use of an even more diverse set of measures to assess each decision-making trait. For example, although we attempted to assess resistance to anchoring and resistance to framing in our study, the measures we used proved to unreliably assess underlying individual differences. This lack of reliability may be because these measures are too context specific or may reflect insufficient power. An example of how to potentially overcome these problems may lie in the resistance to framing component of the adult DMC scale (Bruine de Bruin et al., 2007, 2011), which includes 14 pairs of positively and negatively framed items including both Asian Disease style problems and attribute framing items (e.g., 20% fat or 80% lean).

5.5 Methodological concerns

Our analysis draws attention away from age *per se* as a predictor of performance and focuses instead on underlying capabilities. This distinction is important as there are many determinants of fluid and crystallized intelligence other than age, so that research that examines the effects of age by itself may not clearly identify the causes of performance differences. For example, crystallized intelligence is strongly determined by education and life experiences, so that what appear to be differences due to age-related changes may really be due to cohort differences, for example in the quality and quantity of education. If one looks only at age, one might attribute increases in performance to the wrong variable, even after controlling for years of education.

5.5.1 Cross-sectional versus longitudinal studies

Given recent controversy over the role of cross-sectional studies of mediators of age effects (Lindenberger et al., 2011; Raz & Lindenberger, 2011; Salthouse, 2011), it is worth briefly discussing the potential tradeoffs between cross-sectional and longitudinal studies. For example, although longitudinal studies can rule out certain cohort effects and provide additional

temporal information about changes, they often follow a single cohort for a shorter period of years than the 30 year range we have in our sample. This raises questions about whether longitudinal results generalize to other cohorts and whether the effects hold over longer periods. Longitudinal studies also have to carefully control for potential confounds due to retesting effects and selective attrition (Salthouse, 2010). Ideally, future work would employ both cross-sectional and longitudinal data. Although such work would be resource intensive, we believe that the use of web-based assessment may make it more viable.

5.5.2 Sample comparison

In addition to differences in the age ranges of our older participants, our sample may differ from those in other studies in other ways, perhaps due to selection effects that come with web-based studies. For example, our older participants on average had more years of education, which has been linked to higher scores on cognitive tests (e.g., Ceci & Williams, 1997; Salthouse, 2010). Although our goal was to test the CCH, we can nonetheless compare our sample to samples used by other researchers in aging.

Comparisons of our web-based older participants to similarly aged participants from the Center for Research and Education on Aging and Technology Enhancement (CREATE) participant pool suggest that there was no difference in the levels of education (Baldassi, Weber, Johnson, Czaja, & Nair, 2010), while older participants from Virginia Cognitive Aging Project (VCAP) were slightly more educated (16.2 years of education vs. 15.4; Salthouse, personal communication, December 28, 2011). Both older and younger participants in our study performed worse than similarly aged VCAP participants on the Raven's Progressive Matrices and Letter Set measures, but there were no interactions between sample and age group. Similarly, comparisons of performance on four fluid and crystallized tests to identical in-person tests at CREATE found some mean differences in performance between our web-based participants and their offline participants, but again none of these differences interacted with age (Baldassi et al., 2010). Finally, we screened 93 (57%) older participants using the Telephone Interview of Cognitive Status (TICS), finding that 90% of the older adults tested non-impaired

and 10% ambiguous, and nobody tested either mildly or severely impaired.

6. CONCLUSION

Lay beliefs about age and decision performance are conflicting. One belief sees older people as wiser; another sees them as suffering from deteriorating decision skills. The complementary capabilities hypothesis suggests that there is not only truth to both beliefs, but proposes a mechanism that may help identify when each operates. In our study, we found that older people were somewhat better decision-makers than younger people, partly as a result of older people's higher levels of crystallized intelligence offsetting lower levels of fluid intelligence. Having greater experience and acquired knowledge from a lifetime of decision-making may have provided older people with another way to make good decisions.

The CCH has important implications for matching task environments to decision-makers. For decisions that rely heavily on processing new information, it is likely that the negative effects of aging will outweigh its positive effects relatively early in middle-age. On the other hand, if the decision relies on recognizing previously learned patterns in a stable environment, age may be an advantage. Finally, the multiple pathways to good decisions may suggest ways of modifying a task to improve performance in different age groups. To minimize the impact of declining fluid intelligence, task designers could supplement internal and scarce working memory with external memory aids to alleviate processing loads for older decision-makers. To maximize the role of crystallized intelligence, task designers could provide relevant experience with the task or analogies to similar tasks in which experience exists, akin to providing a more familiar context for the Wason selection task (Cosmides, 1989). Finally, our results make the strong prediction that increases in both fluid and crystallized intelligence produced by training may result in increases in decision performance. This possibility deserves further empirical exploration.

REFERENCES

Ackerman, Phillip L. (2007). New Developments in Understanding Skilled Performance. *Current Directions in Psychological Science, 16*(5), 235-239. doi: 10.1111/j.1467-8721.2007.00511.x

Ackerman, Phillip L., & Beier, Margaret E. (2006). Determinants of domain knowledge and independent study learning in an adult sample. *Journal of Educational Psychology, 98*(2), 366-381. doi: 10.1037/0022-0663.98.2.366

Agarwal, S., Driscoll, J.C., Gabaix, X., & Laibson, D. (2010). The age of reason: financial decisions over the life cycle and implications for regulation. *Brookings Papers on Economic Activity, 2009*(2), 51-117.

Agarwal, S., & Mazumder, B. (2013). Cognitive Abilities and Household Financial Decision Making. *American Economic Journal: Applied Economics, 5*(1), 193-207.

Angeletos, George-Marios, Laibson, David, Repetto, Andrea, Tobacman, Jeremy, & Weinberg, Stephen. (2001). The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical Evaluation. *The Journal of Economic Perspectives, 15*(3), 47-68.

Ariely, D., Loewenstein, G., & Prelec, D. (2003). "Coherent Arbitrariness": Stable Demand Curves Without Stable Preferences. *Quarterly Journal of Economics, 118*(1), 73-105.

Artistico, D., Cervone, D., & Pezzuti, L. (2003). Perceived self-efficacy and everyday problem solving among young and older adults. *Psychology and Aging, 18*, 68-79.

Atlas, S., Johnson, Eric J., & Payne, J.W. (2011). *Bold Borrowing and Deferred Defaults: Impatience and Underwater Mortgages*. Columbia University. New York.

Baldassi, M., Weber, Elke U., Johnson, Eric J., Czaja, S.J., & Nair, S.N. (2010). *Online vs. In-Person Cognitive Function Tests of Younger and Older Adults*. Center for Decision Sciences. Columbia University. New York.

Banks, J., O'Dea, C., & Oldfield, Z. (2010). Cognitive Function, Numeracy and Retirement Saving Trajectories. *The Economic Journal, 120*(548), 381-410.

Besedes, T., Deck, C., Sarangi, S., & Shor, M. (2010). Age effects and heuristic decision making. . *Psychology and Aging, 25*(2).

Bickel, W.K., & Marsch, L.A. (2001). Toward a behavioral economic understanding of drug dependence: delay discounting processes. *Addiction, 96*(1), 73-86.

Browne, M.W., & Cudeck, R. . (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing Structural Models*. Newbury Park, CA: Sage.

Bruine de Bruin, W., Parker, A.M., & Fischhoff, B. (2007). Individual differences in adult decision-making competence. *Journal of Personality and Social Psychology, 92*(5), 938.

Bruine de Bruin, W., Parker, A.M., & Fischhoff, B. (2011). Explaining Adult Age Differences in Decision-making Competence. *Journal of Behavioral Decision Making, In Press*. doi: 10.1002/bdm.712

Carroll, J.B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. New York: Cambridge University Press.

Carstensen, L.L. (2006). The influence of a sense of time on human development. *Science, 312*, 1913-1915.

Carstensen, L.L., Isaacowitz, D.M., & Charles, S.T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist, 54*(3), 165-181.

Cattell, R.B. (1971). *Abilities: Their structure, growth, and action*. New York: Houghton Mifflin.

Cattell, R.B. (1987). *Intelligence: Its structure, growth, and action*. New York: Elsevier Science Pub. Co.

Ceci, Stephen J., & Williams, Wendy M. (1997). Schooling, intelligence, and income. *American Psychologist, 52*(10), 1051-1058. doi: 10.1037/0003-066x.52.10.1051

Chabris, Christopher, Laibson, David, Morris, Carrie, Schuldt, Jonathon, & Taubinsky, Dmitry. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of Risk and Uncertainty, 37*(2), 237-269. doi: 10.1007/s11166-008-9053-x

Chapman, G.B., & Johnson, Eric J. (2002). Incorporating the irrelevant: Anchors in judgments of belief and value. In T. Gilovich, D. Griffin & D. Kahneman (Eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (pp. 120-138). New York, NY: Cambridge University Press.

Charles, S.T., & Carstensen, L.L. (2010). Social and emotional aging. *Annual review of psychology, 61*, 383-409.

Charles, S.T., Mather, M., & Carstensen, L.L. (2003). Aging and emotional memory: The forgettable nature of negative images for older adults. *Journal of Experimental Psychology: General, 132*(2), 310-324. doi: 10.1037/0096-3445.132.2.310

Cosmides, Leda. (1989). The logic of social exchange: Has natural selection shaped how humans reason? Studies with the Wason selection task. *Cognition, 31*(3), 187-276. doi: 10.1016/0010-0277(89)90023-1

Craik, F.I.M., & Salthouse, T.A. (2000). *The Handbook of Aging and Cognition* (2nd ed.). Mahwah, NJ: Erlbaum.

Crawford, John D., & Stankov, Lazar. (1996). Age differences in the realism of confidence judgements: A calibration study using tests of fluid and crystallized intelligence. *Learning and Individual Differences, 8*(2), 83-103. doi: Doi: 10.1016/s1041-6080(96)90027-8

Czaja, S.J., Charness, N., Dijkstra, K., Fisk, A.D., Rogers, W.A., & Sharit, J. (2006). CREATE common core battery of measures: Technical report No. CREATE-2006-01. Atlanta, GA: Center for Research and Education on Aging and Technology Enhancement (CREATE).

Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A., & Sharit, J. (2006). Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging, 21*(2), 333-352.

Damasio, A.R. (1994). *Descartes' error: Emotion, reason, and the human brain*. New York: Avon.

Del Missier, F., Mäntylä, T., & Bruine de Bruin, W. (2011). Decision-making Competence, Executive Functioning, and General Cognitive Abilities. *Journal of Behavioral Decision Making, 24*, forthcoming.

Delavande, A., Rohwedder, S., & Willis, R. (2008). *Preparation for retirement, financial literacy and cognitive resources*. Lisbon, Portugal. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1337655

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are Risk Aversion and Impatience Related to Cognitive Ability? *American Economic Review, 100*(3), 1238–1260.

Dohmen, T., Falk, A., Huffman, D., Sunde, Uwe, Schupp, Jürgen, & Wagner, Gert G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522-550. doi: 10.1111/j.1542-4774.2011.01015.x

Fernandes, Daniel, Lynch Jr, J.G., & Netemeyer, Richard G. (2012). *A Meta-Analytic and Psychometric Investigation of the Effect of Financial Literacy on Downstream Financial Behaviors*. University of Colorado.

Finucane, M.L., Mertz, C.K., Slovic, Paul, & Schmidt, Elizabeth Scholze. (2005). Task Complexity and Older Adults' Decision-Making Competence. *Psychology and Aging, 20*(1), 71-84. doi: 10.1037/0882-7974.20.1.71

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives, 19*(4), 25-42.

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature, 40*(2), 351-401.

Friedman, Naomi P., Miyake, Akira, Corley, Robin P., Young, Susan E., DeFries, John C., & Hewitt, John K. (2006). Not All Executive Functions Are Related to Intelligence. *Psychological Science, 17*(2), 172-179. doi: 10.1111/j.1467-9280.2006.01681.x

Genesove, D., & Mayer, C. (2001). Loss Aversion and Seller Behavior: Evidence from the Housing Market. *Quarterly Journal of Economics, 116*(4), 1233-1260.

Green, L., Fry, A.F., & Myerson, J. (1994). Discounting of delayed rewards: A life-span comparison. *Psychological Science*(5), 33-36.

Grossmann, I., Na, J., Varnum, M. E., Park, D. C., Kitayama, S., & Nisbett, R. E. (2010). Reasoning about social conflicts improves into old age. *Proceedings of the National Academy of Sciences of the United States of America, 107*(16), 7246-7250.

Hambrick, David Z., Salthouse, T.A., & Meinz, Elizabeth J. (1999). Predictors of Crossword Puzzle Proficiency and Moderators of Age-Cognition Relations. *Journal of Experimental Psychology: General, 128*(2), 131-164.

Hanoch, Y., Wood, S., & Rice, T. (2007). Bounded Rationality, Emotions and Older Adult Decision Making: Not So Fast and Yet So Frugal. *Human Development, 50*(6), 333-358.

Hardie, B.G.S., Johnson, Eric J., & Fader, P.S. (1993). Modeling loss aversion and reference dependence effects on brand choice. *Marketing Science*, 378-394.

Hastings, J., & Tejeda-Ashton, L. (2008). Financial Literacy, Information and Demand Elasticity: Survey and Experimental Evidence from Mexico. NBER Working Paper No. 14538.

Henninger, D.E., Madden, D.J., & Huettel, S.A. (2010). Processing Speed and Memory Mediate Age-Related Differences in Decision Making. *Psychology and Aging, 25*(2), 262-270. doi: 10.1037/a0019096

Hess, T.M. (2000). Aging-related constraints and adaptations in social information processing. In U. V. Hecker, S. Dutke & G. Sedek (Eds.), *Generative mental processes and cognitive resources: Integrative research on adaptation and control* (pp. 129-155). Dordrecht, The Netherlands: Kluwer.

Hess, T.M., McGee, K.A., Woodburn, S.M., & Bolstad, C.A. (1998). Age-related priming effects in social judgments. *Psychology and Aging, 13*, 127-137.

Hess, T.M., Rosenberg, D.C., & Waters, S.J. (2001). Motivation and representational processes in adulthood: The effects of social accountability and information relevance. *Psychology and Aging, 16*, 629-642.

Hess, T.M., Waters, S.J., & Bolstad, C.A. (2000). Motivational and cognitive influences on affective priming in adulthood. *Journal of Gerontology: Psychological Sciences, 55B*, 193-204.

Hilgert, M.A., Hogarth, J.M., & Beverly, S.G. (2003). Household financial management: The connection between knowledge and behavior. *Federal Reserve Bulletin*(Jul), 309-322.

Horn, J.L., & Cattell, R.B. (1967). Age differences in fluid and crystallized intelligence. *Acta Psychologica, 26*, 107-129. doi: http://dx.doi.org/10.1016/0001-6918(67)90011-X

Hu, L., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Isaacowitz, D. M., Allard, E. S., Murphy, N. A., & Schlangel, M. (2009). The time course of age-related preferences toward positive and negative stimuli. *The journals of gerontology. Series B, Psychological sciences and social sciences, 64*(2), 188-192.

Jacoby, L.L. (1999). Ironic effects of repetition: Measuring age-related differences in memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25*, 3-22.

Johnson, Eric J., Hershey, J., Meszaros, J., & Kunreuther, H. (1993). Framing, probability distortions, and insurance decisions. *Journal of Risk and Uncertainty, 7*(1), 35-51. doi: 10.1007/bf01065313

Khwaja, A, Silverman, D, & Sloan, F. (2007). Time preference, time discounting, and smoking decisions *Journal of Health Economics, 26*(5), 927-949.

Kim, S., Goldstein, D., Hasher, L., & Zacks, R.T. (2005). Framing effects in young and old adults. *Journal of Gerontology: Psychological Sciences, 60B*, 215-218.

Kim, S., & Hasher, L. (2005). The attraction effect in decision making: Superior performance by older adults. *Quarterly Journal of Experimental Psychology, 58A*, 120-133.

Kline, R.B. (2010). *Principles and Practice of Structural Equation Modeling* (3rd ed.). New York: Guilford Press.

Kovalchik, S., Camerer, C.F., Grether, D.M., Plott, C.R., & Allman, J.M. (2005). Aging and decision-making: A comparison between neurologically healthy elderly and young individuals. *Journal of Economic Behavior & Organization, 58*, 79-94.

Labouvie-Vief, G. (2003). Dynamic integration: Affect, cognition, and the self in adulthood. *Current Directions in Psychological Science, 12*, 201-206.

Li, Shu-Chen, Lindenberger, Ulman, Hommel, Bernhard, Aschersleben, Gisa, Prinz, Wolfgang, & Baltes, Paul B. (2004). Transformations in the Couplings Among Intellectual Abilities and Constituent Cognitive Processes Across the Life Span. *Psychological Science, 15*(3), 155-163. doi: 10.1111/j.0956-7976.2004.01503003.x

Lindenberger, Ulman, Mayr, Ulrich, & Kliegl, Reinhold. (1993). Speed and intelligence in old age. *Psychology and Aging, 8*(2), 207-220. doi: 10.1037/0882-7974.8.2.207

Lindenberger, Ulman, & Pötter, Ulrich. (1998). The complex nature of unique and shared effects in hierarchical linear regression: Implications for developmental psychology. *Psychological Methods, 3*, 218-230.

Lindenberger, Ulman, von Oertzen, Timo, Ghisletta, Paolo, & Hertzog, Christopher. (2011). Cross-sectional age variance extraction: What's change got to do with it? *Psychology and Aging, 26*(1), 34-47. doi: 10.1037/a0020525

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General Performance on a Numeracy Scale among Highly Educated Samples. *Medical Decision Making, 21*, 37-44.

Lusardi, A., & Mitchell, O.S. (2006). *Financial Literacy and Planning: Implications for Retirement Wellbeing*. Pension Research Council. Wharton School, University of Pennsylvania.

Lusardi, A., & Mitchell, O.S. (2007). Baby Boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of Monetary Economics, 54*(1), 205-224. doi: 10.1016/j.jmoneco.2006.12.001

Lusardi, A., & Mitchell, O.S. (2009). How Ordinary People Make Complex Economics Decisions: Financial Literacy and Retirement Readiness. *NBER Working Paper, 15350*.

Lusardi, A., & Mitchell, O.S. (2011). Financial literacy around the world: An overview. *Journal of Pension Economics and Finance, 10*(4), 497-508.

Lusardi, A., & Tufano, P. (2009). *Debt Literacy, Financial Experiences, and Overindebtedness*. Retrieved from http://www.dartmouth.edu/~alusardi/Papers/Lusardi_Tufano.pdf

MacPherson, S.E., Phillips, L.H., & Della Sala, S. (2002). Age, executive function and social decision making: A dorsolateral prefrontal theory of cognitive aging. *Psychology and Aging, 17*, 598-609.

Mata, Rui, & Nunes, L. (2010). When less is enough: Cognitive aging, information search, and decision quality in consumer choice. *Psychology and Aging, 25*(2), 289-298.

Mata, Rui, Schooler, Lael J., & Rieskamp, Jörg. (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging, 22*(4), 796-810. doi: 10.1037/0882-7974.22.4.796

Mather, M. (2006). A review of decision-making processes: Weighing the risks and benefits of aging. In L. L. Carstensen & C. R. Hartel (Eds.), *When I'm 64* (pp. 145-173). Washington, DC.: National Academy Press.

Mather, M., & Carstensen, L.L. (2005). Aging and motivated cognition: The positivity effect in attention and memory. *Trends in Cognitive Sciences, 9*(10), 496-502.

Maxwell, Scott E., & Cole, David A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods, 12*(1), 23-44. doi: 10.1037/1082-989x.12.1.23

Mayhorn, C.B., Fisk, A.D., & Whittle, J.D. (2002). Decision, decisions: Analysis of age, cohort, and time of testing on framing of risky decision options. *Human Factors, 44*, 515-521.

McArdle, J.J., Ferrer-Caja, Emilio, Hamagami, Fumiaki, & Woodcock, R.W. (2002). Comparative longitudinal structural analyses of the growth and decline of multiple intellectual abilities over the life span. *Developmental Psychology, 38*(1), 115-142. doi: 10.1037/0012-1649.38.1.115

McArdle, J.J., Smith, J.P., & Willis, R. (2009). *Cognition and Economic Outcomes in the Health and Retirement Survey*. IZA Discussion Paper, (4269).

McArdle, J.J., & Woodcock, R.W. (2009). *Adaptive testing with selected Woodcock cognitive tests*. Longitudinal Research Institute. Charlottesville, VA.

McNeil, Barbara J., Pauker, Stephen G., Sox, Harold C., & Tversky, Amos. (1982). On the Elicitation of Preferences for Alternative Therapies. *New England Journal of Medicine, 306*(21), 1259-1262. doi: doi:10.1056/NEJM198205273062103

Meier, Stephan, & Sprenger, Charles D. (2010). Present-Biased Preferences and Credit Card Borrowing. *American Economic Journal: Applied Economics, 2*(1), 193-210.

Meier, Stephan, & Sprenger, Charles D. (2013). *Temporal Stability of Time Preferences*. Graduate School of Business. Columbia University. New York.

Muthén, LK, & Muthén, BO. (2010). Mplus (Version 6). Los Angeles, CA: Muthén & Muthén.

Nunes, J.C., & Boatwright, P. (2004). Incidental prices and their effect on willingness to pay. *Journal of Marketing Research, 41*(4), 457-466.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance, 53*(5), 1775-1798.

Peters, E., Finucane, M.L., MacGregor, D.G., & Slovic, P. (2000). The bearable lightness of aging: Judgement and decision processes in older adults. In P. Stern & L. L. Carstensen (Eds.), *The Aging Mind: Opportunities in Cognitive Research* (pp. 144-165). Washington, DC: National Academies Press.

Peters, E., Hess, T.M., Vaestfjaell, D., & Auman, C. (2007). Adult age differences in dual information processes: Implications for the role of affective and deliberative processes in older adults' decision making. *Perspectives on Psychological Science, 2*, 1-23.

Preacher, K.J., & Hayes, A.F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879-891.

Queen, T.L., & Hess, T.M. (2010). Age differences in the effects of conscious and unconscious thought in decision making. *Psychology and Aging, 25*(2), 251-261.

Ratcliff, Roger, Thapar, Anjali, & McKoon, Gail. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology, 60*(3), 127-157. doi: 10.1016/j.cogpsych.2009.09.001

Raz, Naftali, & Lindenberger, Ulman. (2011). Only time will tell: Cross-sectional studies offer
    no solution to the age–brain–cognition triangle: Comment on Salthouse (2011).
    Psychological Bulletin, 137(5), 790-795. doi: 10.1037/a0024503

Read, D., & Read, N.L. (2004). Time discounting over the lifespan. *Organizational Behavior
    and Human Decision Processes, 94*(1), 22-32. doi: DOI: 10.1016/j.obhdp.2004.01.002

Reimers, S., Maylor, E.A., Stewart, N., & Chater, N. (2009). Associations between a one-shot
    delay discounting measure and age, income, education and real-world impulsive behavior.
    Personality and Individual Differences, 47, 973-978.

Reips, Ulf-Dietrich. (2002). Standards for Internet-Based Experimenting. *Experimental
    Psychology, 49*(4), 243-256. doi: 10.1026//1618-3169.49.4.243

Roennlund, M., Karlsson, E., Laggnaess, E., Larsson, L., & Lindstroem, T. (2005). Risky
    decision making across three arenas of choice: Are younger and older adults differently
    susceptible to framing effects? *Journal of General Psychology, 132*, 81-92.

Rothman, Alexander J., & Salovey, Peter. (1997). Shaping perceptions to motivate healthy
    behavior: The role of message framing. *Psychological Bulletin, 121*(1), 3-19. doi:
    10.1037/0033-2909.121.1.3

Salthouse, T.A. (1991). Mediation of adult age differences in cognition by reductions in working
    memory and speed of processing. *Psychological Science, 2*, 179-183.

Salthouse, T.A. (1992). Why do adult age differences increase with task complexity? .
    Developmental Psychology, 28, 905-918.

Salthouse, T.A. (1993). Speed mediation of adult age differences in cognition *Developmental
    Psychology, 29*, 722-738.

Salthouse, T.A. (1994). The nature of the influence of speed on adult age differences in cognition.
    Developmental Psychology, 30, 240-259.

Salthouse, T.A. (1996). The processing-speed theory of adult age differences in cognition.
    Psychological Review, 103, 403-428.

Salthouse, T.A. (2004). What and when of cognitive aging. *Current Directions in Psychological
    Science, 13*(4), 140-144.

Salthouse, T.A. (2006). Mental exercise and mental aging: Evaluating the validity of the "use it
    or lose it" hypothesis. *Perspectives on Psychological Science, 1*, 68-87.

Salthouse, T.A. (2010). *Major Issues in Cognitive Aging*. New York: Oxford University Press.

Salthouse, T.A. (2011). All data collection and analysis methods have limitations: Reply to Rabbitt (2011) and Raz and Lindenberger (2011). *Psychological Bulletin, 137*(5), 796-799. doi: 10.1037/a0024843

Salthouse, T.A., Atkinson, T.M., & Berish, D.E. (2003). Executive Functioning as a Potential Mediator of Age-Related Cognitive Decline in Normal Adults. *Journal of experimental psychology: General, 132*(4), 566-594. doi: 10.1037/0096-3445.132.4.566

Salthouse, T.A., Pink, J.E., & Tucker-Drop, E.M. (2008). Contextual analysis of fluid intelligence. *Intelligence, 36*, 464-486.

Samanez-Larkin, G.R., & Carstensen, L.L. (2011). Socioemotional functioning and the aging brain. In J. Decety & J. T. Cacioppo (Eds.), *The Handbook of Social Neuroscience*. New York: Oxford University Press.

Samanez-Larkin, G.R., Gibbs, S.E.B., Khanna, K., Nielsen, L., Carstensen, L.L., & Knutson, B. (2007). Anticipation of monetary gain but not loss in healthy older adults. *Nature Neuroscience, 10*(6), 787-791.

Schaie, K. Warner. (1993). The Seattle Longitudinal Studies of Adult Intelligence. *Current Directions in Psychological Science, 2*(6), 171-175.

Schmiedek, Florian, & Li, Shu-Chen. (2004). Toward an Alternative Representation for Disentangling Age-Associated Differences in General and Specific Cognitive Abilities. *Psychology and Aging, 19*(1), 40.

Shamosh, N.A., & Gray, J.R. (2008). Delay discounting and intelligence: A meta-analysis. *Intelligence, 36*(4), 289-305.

Shrout, P.E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods, 7*(4), 422-445.

Simonson, I., & Drolet, A. (2004). Anchoring effects on consumers' willingness-to-pay and willingness-to-accept. *Journal of Consumer Research*, 681-690.

Simonton, Dean Keith. (1997). Creative productivity: A predictive and explanatory model of career trajectories and landmarks. *Psychological Review, 104*(1), 66-89. doi: 10.1037/0033-295x.104.1.66

Smith, J.P., McArdle, J.J., & Willis, R. (2010). Financial Decision Making and Cognition in a Family Context. *The Economic Journal, 120*(548), 363-380.

Souzou, P.D., & Seymour, R.M. (2003). Augmented discounting: interaction between aging and time-preference behavior. *Proceedings of the Royal Society of London: Biology, 270*(1519), 1047-1053.

Steiger, J.H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate behavioral research, 25*(2), 173-180.

Stewart, N. (2009). The cost of anchoring on credit-card minimum repayments. *Psychological Science, 20*(1), 39.

Strough, J.N., Mehta, C.M., McFall, J.P., & Schuller, K.L. (2008). Are older adults less subject to the sunk-cost fallacy than younger adults? *Association for Psychological Science, 19*(7), 650-652.

Tentori, K., Osherson, D., Hasher, L., & May, C.P. (2001). Wisdom and aging: Irrational preferences in college students but not older adults. *Cognition, 81*, 87-96.

Thornton, W.J., & Dumke, H.A. (2005). Age differences in everyday problem-solving and decision-making effectiveness: A meta-analytic review. *Psychology and Aging, 20*(1), 85-99.

Trostel, P.A, & Taylor, G.A. (2001). A theory of time preference. *Economic Inquiry, 39*, 379-395.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*(4481), 453-458.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference dependent model. *Quarterly Journal of Economics, 107*(4), 1039-1061.

United Nations. (2002). World population ageing: 1950–2050. Retrieved 3-9-2011, from http://www.un.org/esa/population/publications/worldageing19502050/

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*.

Vandenberg, Robert J., & Lance, Charles E. (2000). A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research. *Organizational Research Methods, 3*(1), 4-70. doi: 10.1177/109442810031002

Wansink, Brian, Kent, Robert J., & Hoch, Stephen J. (1998). An Anchoring and Adjustment Model of Purchase Quantity Decisions. *Journal of Marketing Research, 35*(1), 71-81.

Weber, Elke U., & Lindemann, Patricia G. (2007). From intuition to analysis: Making decisions with our head, our heart, or by the book. In H. Plessner, C. Betsch & T. Betsch (Eds.), *Intuition in judgment and decision making* (pp. 191-208). Mahwah, NJ: Lawrence Erlbaum.

Wechsler, D. (1997). *Wechsler Adult Intelligence Scale III (3rd ed.)*. San Antonio, TX: The Psychological Corporation.

Weller, Rosalyn E., Cook, Edwin W., Avsar, Kathy B., & Cox, James E. (2008). Obese women show greater delay discounting than healthy-weight women. *Appetite, 51*(3), 563-569. doi: DOI: 10.1016/j.appet.2008.04.010

Willman, P., Fenton-O'Creevy, M., Nicholson, N., & Soane, E. (2002). Traders, managers and loss aversion in investment banking: a field study. *Accounting, organizations and society, 27*(1-2), 85-98.

Wood, S., Busemeyer, J., Koling, A., Cox, C., & Davis, H. (2005). Older adults as adaptive decision makers: Evidence from the Iowa gambling task. *Psychology and Aging, 20*, 220-225.

Zacks, R.T., Hasher, L., & Li, K.Z.H. (2000). Human memory. In F. I. M. Craik & T. A. Salthouse (Eds.), *The Handbook of Aging and Cognition* (2nd ed., pp. 293-357). Mahwah, NJ: Erlbaum.

Zhao, X., Lynch, J.G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research, 37*(2), 197-206.

Figure 1. Complementary competencies hypothesis of age differences in decision performance.

$a_{G_c} \times b_{G_c} > 0$

Positive indirect effect
(Age is a benefit)

$a_{G_f} \times b_{G_f} < 0$

Negative indirect effect
(Age is a detriment)
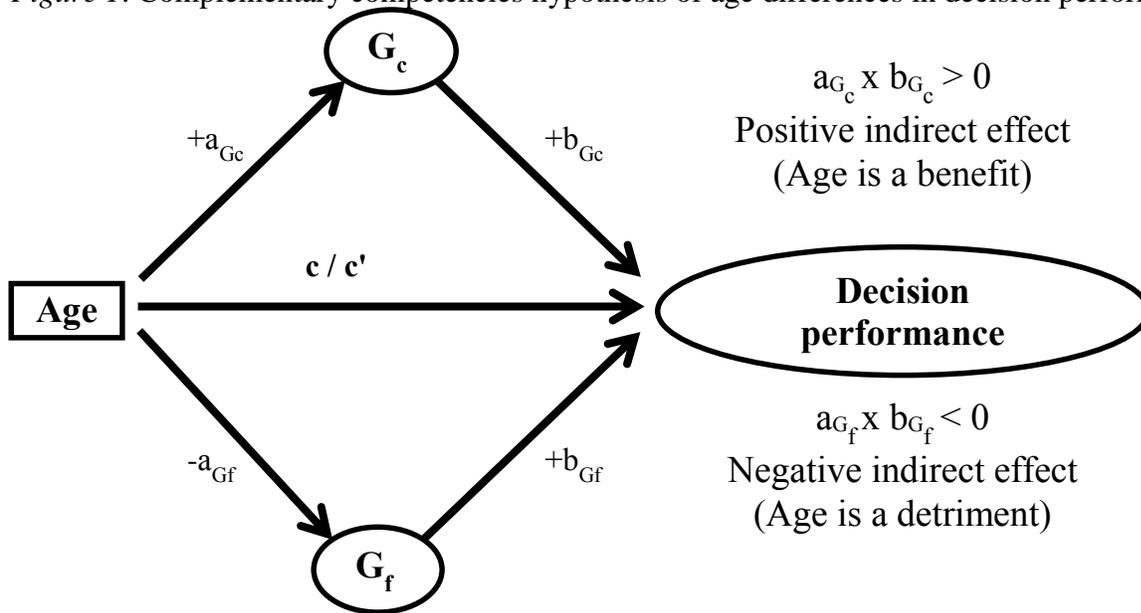
Figure 2. Cognitive capabilities measurement model: Factor loadings and inter-factor correlation.
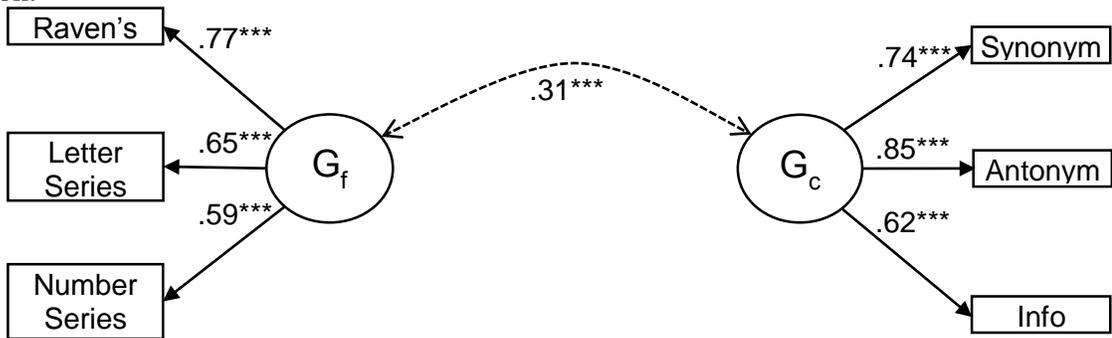
Figure 3. Decision-making factor loadings and inter-factor correlations.
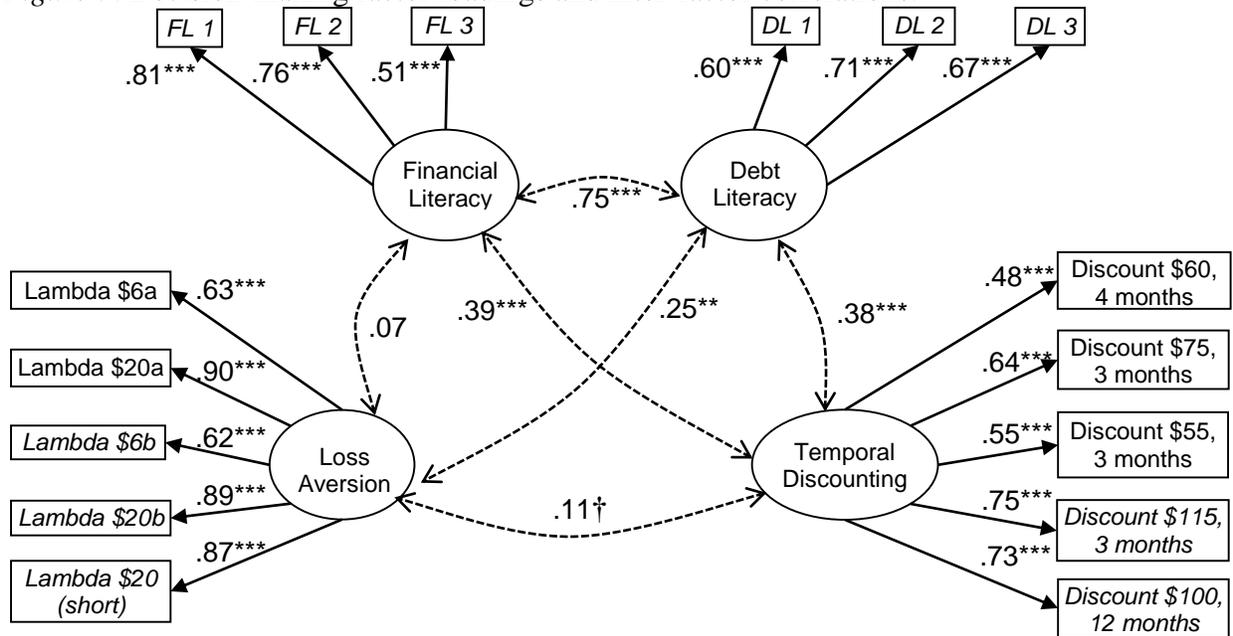
Note: Tasks in italics were run in the fourth wave, one year after the first wave. *** < .001

Figure 4. Decision performance relative to 21-year-olds over the life span using our estimated relationships and extrapolated using data from Salthouse (2004).
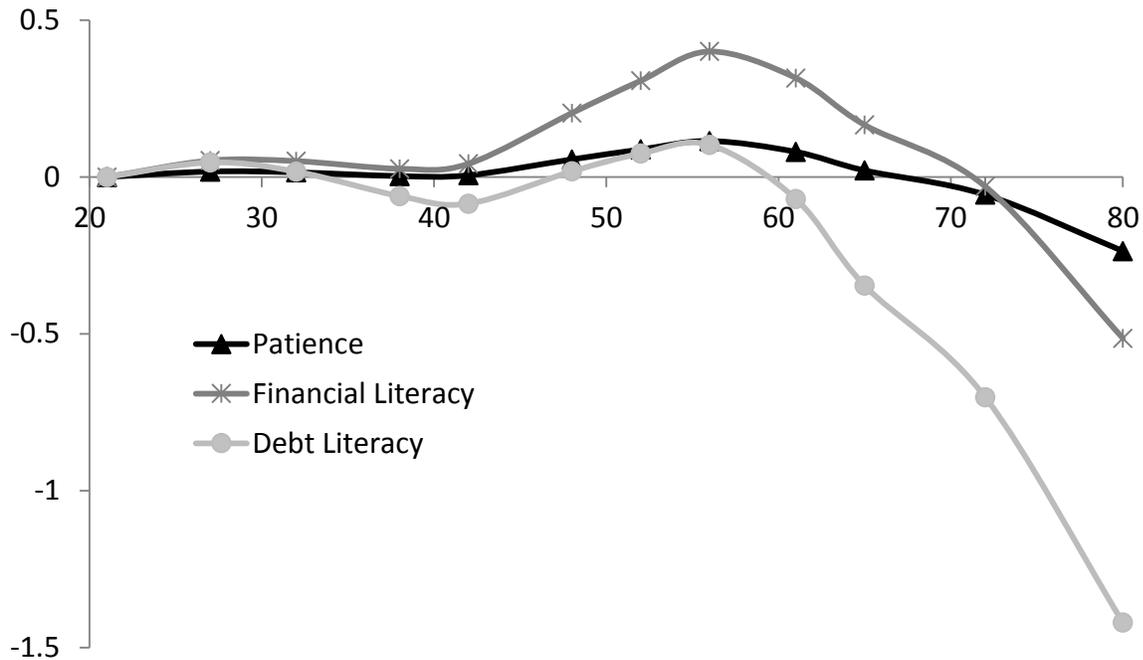
Note: The exact shape of these curves depends on the standard errors of the estimated age trajectories in Salthouse (2004), the standard errors of the regression weights, and potential age differences in the regression weights. We therefore urge caution in interpreting the exact ages at which decision performance peaks in these curves.

Table 1. Percentage of respondents in younger and older adult sample in each socioeconomic category.

		Young	Old
Gender	Percent female	67.1	64.4
Education	No degree	0.0	1.2
	High school diploma	33.5	24.5
	Associate degree, occupational	2.3	6.8
	Associate degree, academic	9.3	8.0
	Bachelor's degree	39.9	33.1
	Master's degree	12.7	17.8
	Professional degree	1.2	1.8
	Doctoral degree	1.2	6.8
Income	Less than $19,999	20.9	6.3
	$20,000 - $34,999	16.9	24.4
	$35,000 - $49,999	17.4	23.1
	$50,000- $99,999	30.8	38.1
	$100,000 - $199,999	11.1	7.5
	Greater than $200,000	2.9	0.6
N		173	163

Table 2. All cognitive and decision-making measures.

Category	Task	Number of Measures or Items	Wave(s)
Decision Making	Resistance to anchors	4 (2 low and 2 high)	1, 4
	Discounting	5 titrators	1, 3, 4
	Loss aversion	5 titrators	1, 3, 4
	Resistance to framing	4 items (2 pairs)	1, 4
	Financial literacy	4	4
	Debt literacy	3	4
Fluid Intelligence	Raven's Progressive Matrices	18	4
	Letter Series	15	4
	Number Series	6 (adaptive)	4
	Cognitive Reflection Test	3	1
	Numeracy	11	1
Crystallized Intelligence	Shipley's Vocabulary	40	2
	Antonym Vocabulary	10	4
	WAIS Information	28	4

Table 3. Means and standard deviations for all measures as a function of age group, and correlations between measures across both age groups.

Measures	Mean Young	Mean Old	SD Young	SD Old	p(old≠young)	Raven	Letter Series	Number Series	CRT	Numeracy	Shipley	Antonym	Info	D $60, 4m	D $75, 3m	D $55, 3m	D $115, 12m	D $100, 12m	LA $6a	LA $20a	LA $6b	LA $20b	LA $20c	Anc H1	Anc L1	Anc H2	Anc L2	Frame 1	Frame 2	FL1	FL2	FL3	DL1	DL2
Raven's Matrices	8.15	5.17	3.67	3.55	p<.001	-																												
Letter Series	10.36	9.50	3.00	2.72	p<.001	**0.49*****	-																												
Number Series	12.00	10.10	3.16	3.38	p<.001	**0.45*****	**0.23*****	-																											
Cognitive Reflection Test	1.23	0.98	1.12	1.05	p<.01	**0.42*****	**0.31*****	**0.43*****	-																										
Numeracy	8.88	8.36	2.14	2.11	p<.01	**0.43*****	**0.32*****	**0.38*****	**0.53*****	-																								
Shipley's Vocabulary	22.63	30.65	9.14	8.92	p<.001	0.07	0.11*	0.01	0.21***	0.22***	-																								
Antonym Vocabulary	4.95	7.02	2.80	2.98	p<.001	0.14*	0.28***	0.15**	0.19***	0.23***	**0.63*****	-																						
WAIS Information	19.76	21.46	4.38	4.17	p<.001	0.23***	0.30***	0.22***	0.30***	0.34***	**0.46*****	**0.51*****	-																					
Discount $60, 4 months	0.43	0.48	0.27	0.29	p<.10	-0.02	0.05	0.00	0.01	0.07	0.05	0.17**	0.10†	-																				
Discount $75, 3 months	0.45	0.54	0.26	0.28	p<.01	-0.03	0.08	0.05	0.07	0.08	0.11*	0.20***	0.12*	**0.62*****	-																		
Discount $55, 3 months	0.44	0.46	0.24	0.25	ns	-0.03	0.05	-0.01	-0.01	-0.02	0.03	0.10†	0.03	**0.68*****	**0.56*****	-																	
Discount $115, 3 months	0.54	0.56	0.24	0.26	ns	0.09	0.12*	0.12*	0.19***	0.19***	0.10†	0.18**	0.22***	**0.37*****	**0.51*****	**0.40*****	-																
Discount $100, 12 months	0.70	0.72	0.15	0.15	ns	0.04	0.06	0.09	0.18**	0.13*	0.01	0.07	0.19**	**0.34*****	**0.37*****	**0.33*****	**0.50*****	-															
Loss Aversion $6a	2.56	2.56	2.12	2.33	ns	-0.01	0.04	0.13*	0.06	0.10†	0.06	-0.05	0.12*	0.03	0.00	0.05	0.04	0.15*	-													
Loss Aversion $20a	2.34	2.25	1.35	1.41	ns	-0.04	-0.04	0.04	0.05	0.05	-0.01	-0.05	0.06	0.07	0.05	0.11*	0.07	0.16**	**0.77*****	-												
Loss Aversion $6b	2.69	2.46	2.19	2.12	ns	-0.08	-0.06	0.09	0.02	0.01	0.00	-0.01	0.05	0.00	0.01	0.04	0.00	0.16**	**0.59*****	**0.53*****	-										
Loss Aversion $20b	2.80	2.68	2.05	2.14	ns	-0.06	-0.08	0.08	0.00	-0.01	0.01	-0.03	0.03	0.03	0.06	0.06	0.00	0.11†	**0.53*****	**0.50*****	**0.83*****	-									
Loss Aversion $20c	2.81	2.81	2.16	2.19	ns	-0.03	-0.08	0.09	0.07	0.02	-0.01	-0.08	0.06	0.07	0.05	0.06	0.03	0.20**	**0.52*****	**0.52*****	**0.76*****	**0.83*****	-								
Anchoring High 1	-0.24	0.25	0.90	1.00	p<.001	-0.12*	-0.06	0.04	0.05	0.04	0.15**	0.12*	0.06	0.07	0.08	0.05	0.02	0.09	0.06	-0.03	-0.10†	-0.02	0.00	-							
Anchoring Low 1	-0.09	0.09	1.06	1.00	ns	-0.02	0.00	0.07	0.13*	0.05	0.06	-0.03	0.14*	0.02	0.08	0.03	-0.01	0.10†	0.07	0.05	0.01	0.02	0.02	**0.12***	-						
Anchoring High 2	-0.04	0.05	1.02	1.00	ns	-0.03	-0.05	-0.07	0.01	0.00	0.03	0.08	0.08	-0.04	-0.07	0.02	0.00	-0.02	-0.05	-0.02	-0.07	-0.09	-0.03	**0.15***	**-0.03**	-					
Anchoring Low 2	-0.09	0.09	0.89	1.00	ns	-0.01	-0.04	-0.09	-0.11	-0.04	0.07	0.05	0.06	-0.02	0.04	0.07	-0.01	-0.07	-0.13†	-0.05	-0.09	-0.12†	-0.11	**0.04**	**0.11**	**0.03**	-				
Resistance to Framing 1	0.48	0.52	0.50	0.50	ns	0.08	0.08	0.02	0.00	0.07	0.05	0.07	0.12*	0.02	0.01	0.02	0.01	0.02	0.00	-0.05	-0.05	-0.05	-0.09	-0.03	-0.03	-0.11†	0.13†	-			
Resistance to Framing 2	0.57	0.59	0.50	0.49	ns	-0.02	-0.01	-0.04	0.00	0.02	0.04	-0.07	-0.03	0.06	0.01	0.08	0.03	0.05	0.02	0.07	-0.02	-0.05	-0.01	-0.11†	-0.03	-0.06	-0.12†	**-0.05**	-		
Financial Literacy 1	0.74	0.93	0.44	0.38	p<.001	0.06	0.15**	0.11*	0.19***	0.21***	0.30***	0.32***	0.25***	0.12*	0.13*	0.07	0.19***	0.16**	-0.03	0.02	0.03	0.00	0.01	0.06	0.05	0.15*	-0.04	-0.01	-0.09	-	
Financial Literacy 2	0.55	0.86	0.50	0.46	p<.001	0.02	0.15**	0.00	0.18***	0.19***	0.29***	0.30***	0.32***	0.08	0.15**	0.07	0.22***	0.19**	0.05	0.08	-0.01	0.02	0.01	0.12*	0.08	0.06	0.02	0.06	-0.06	**0.40*****	-
Financial Literacy 3	0.65	0.75	0.48	0.49	p<.05	0.11†	0.02	0.13*	0.18***	0.17**	0.14*	0.16**	0.24***	0.06	0.12*	0.03	0.13*	0.17**	0.03	0.05	0.05	0.05	0.07	0.06	0.11*	-0.02	-0.03	0.05	-0.09†	**0.21*****	**0.21*****
Debt Literacy 1	0.50	0.57	0.50	0.46	ns	0.24***	0.23***	0.25***	0.39***	0.30***	0.25***	0.24***	0.26***	0.07	0.09	0.04	0.18**	0.12*	0.07	0.11†	0.03	-0.01	-0.01	0.07	0.04	-0.07	-0.09	0.07	0.04	0.21***	0.23***

Note: last column (DL2) value for Debt Literacy 1 row continues: 0.19*** -

| Debt Literacy 2 | 0.37 | 0.52 | 0.48 | 0.50 | p<.01 | 0.11* | 0.18** | 0.21*** | 0.30*** | 0.28*** | 0.20*** | 0.24*** | 0.27*** | 0.12* | 0.12* | 0.13* | 0.18** | 0.16** | 0.05 | 0.07 | 0.10† | 0.09† | 0.09 | 0.10† | 0.09 | 0.01 | -0.05 | 0.00 | 0.06 | 0.28*** | 0.25*** | 0.16** | **0.33*** | - |
| Debt Literacy 3 | 0.10 | 0.17 | 0.30 | 0.50 | p<.10 | 0.08 | 0.04 | 0.07 | 0.21*** | 0.22*** | 0.05 | 0.15** | 0.16** | 0.12* | 0.11* | 0.17** | 0.07 | 0.19** | 0.20*** | 0.17** | 0.17** | 0.19*** | 0.18** | 0.13* | 0.04 | 0.06 | 0.00 | 0.02 | -0.01 | 0.01 | 0.12* | 0.12* | **0.22*** | **0.15** |

Note: Higher values correspond to better performance for all variables. Loss aversion means are shown without reverse coding, so smaller values (closer to one) are better. Anchor scores were standardized and averaged across questions. Correlations between cognitive measures in the same capability group are shown in bold.

†<.10, *<.05, **<.01, ***<.001

Table 4. Multiple-group analysis for younger and older cognitive factor invariance.

Model	d.f.	χ^2	RMSEA	CFI	$\Delta\chi^2/\,\Delta$d.f.
M1: No constraints	16	30.89	.069	.972	-
M2: M1 + Equal loadings across age groups	20	42.98	.083	.950	12.09/4, *p* < .05
M2': M1 + Equal loadings except Raven's	19	37.07	.075	.961	6.18/3, *ns*
M3: M2' + Equal intercepts	23	65.20	.104	.908	28.13/4, *p* < .0001
M3': M2' + Equal intercepts except Raven's	22	42.60	.078	.953	4.53/3, *ns*
M4: M3' + Equal factor variances and covariances	25	44.83	.072	.955	2.23/3, *ns*

Note: χ^2 difference tests for each model in the rightmost column are relative to the model above it, except for model M2', which is compared to model M1, and M3', which is compared to M2'.

Table 5. Multiple-group analysis for younger and older decision-making factor invariance.

Model	d.f.	χ^2	RMSEA	CFI	$\Delta\chi^2/\Delta$d.f.
DM1: No constraints	196	243.88	.038	.940	-
DM2: DM1 + Equal factor loadings across age groups	206	253.37	.037	.940	11.11/10, *ns*
DM3: DM2 + Equal factor intercepts	216	267.21	.038	.935	14.74/10, *ns*
DM4: DM3 + Equal factor variances and covariances	226	288.72	.041	.921	19.30/10, *p* < .05
DM4': DM3 + Equal factor variances (except financial literacy) and covariances	225	270.99	.035	.942	12.51/9, *ns*

Note: χ^2 difference tests calculated by Mplus using Satorra-Bentler Scaled Chi-Square (http://www.statmodel.com/chidiff.shtml).

Table 6. Standardized coefficients for decision-making factors as a function of cognitive factors, age, and demographics, and the cognitive factors as a function of demographics aside from age.

Decision-making Factor	G_f	G_c	Age	Male	Income	Education
Temporal Discounting	.13†	.15*	.08	.07	.13‡	.09
Loss Aversion	-.01	-.08	.06	.20**	.09†	.09‡
Financial Literacy	.35***	.45***	.41***	.13†	.12†	.10
Debt Literacy	.52***	.42***	.19*	.33***	.01	-.02
G_f				.08	.09	.11†
G_c				-.04	-.09	.33***

Note. ‡ < .15, † < .10, * < .05, ** < .01, *** < .001

Table 7. Standardized coefficients for direct, indirect, and total effects of age on decision performance.

Decision-making Factor	Indirect Effect via G_f	Indirect Effect via G_c	Total Indirect Effect	Direct Effect of Age	Total Effect of Age	Male	Income	Education
Label in Figure 1	$a_{Gf} \times b_{Gf}$	$a_{Gc} \times b_{Gc}$	$\sum a_i \times b_i$	c'	c			
Temporal Discounting	-.08†	.08*	.007	.07	.08	.07	.13‡	.09
Loss Aversion	.01	-.04	-.03	.09	.06	.20**	.09†	.09‡
Financial Literacy	-.21***	.25***	.04	.37***	.41***	.13†	.12†	.10
Debt Literacy	-.31***	.23***	-.08	.27**	.19*	.33***	.01	-.02
G_f					-.52***	.07	.07	.09‡
G_c					.47***	-.02	-.08‡	.29***

Note. ‡ < .15, † < .10, * < .05, ** < .01, *** < .001

Table 8. Factor loadings and correlations with age for Schmiedek & Li (2004) analysis.

Variable	Factor					
	Fluid Intelligence	Crystallized Intelligence	Temporal Discounting	Loss Aversion	Financial Literacy	Debt Literacy
Raven's Matrices	0.676***					
Letter Series	0.692***					
Number Series	0.595***					
Shipley's Vocabulary		0.626***				
Antonym Vocabulary		0.713***				
WAIS Information		0.707***				
Discount $60, 4 months	0.148*	0.152*	0.682***			
Discount $75, 3 months	0.054	0.220**	0.721***			
Discount $55, 3 months	0.150*	0.086	0.729***			
Discount $115, 3 months	0.248**	0.233**	0.577***			
Discount $100, 12 months	0.110‡	0.189*	0.574***			
Loss Aversion $6a	0.029	0.033		0.725***		
Loss Aversion $20a	-0.054	0.054		0.711***		
Loss Aversion $6b	-0.079	0.016		0.863***		
Loss Aversion $20b	-0.086	0.014		0.847***		
Loss Aversion $20c	-0.054	-0.007		0.830***		
Financial Literacy 1	0.054	0.675***			0.355*	
Financial Literacy 2	0.150†	0.648***			0.408***	
Financial Literacy 3	0.257**	0.325**			0.420**	
Debt Literacy 1	0.300***	0.313***				0.277**
Debt Literacy 2	0.144†	0.401***				0.344**
Debt Literacy 3	0.194*	0.172‡				0.912***
Correlation with Age	-0.455***	0.426***	-0.002	0.049	0.083	0.174*

Note: ‡ < .15, † < .10, * < .05, ** < .01, *** < .001

Complementary Cognitive Competencies, Economic Decision-Making, and Aging

Ye Li, Martine Baldassi, Eric J. Johnson, and Elke U. Weber

Supplemental Materials

1. DESCRIPTIONS OF ALL TASKS

1.1 Decision-Making Measures

Temporal discounting was measured with five choice titrators (Green, Fry, & Myerson, 1994). These titrators used both "delay" and "accelerate" frames: The delay frame presented participants with a series of choices between a fixed smaller gift certificate today and varying amounts of a larger gift certificate at a fixed time in the future, thus allowing participants to receive more money at the cost of delayed payment. The accelerate frame instead fixed the larger, future gift certificate and varied the amount of the smaller gift certificate today, thus allowing participants to accelerate payment at the cost of receiving less money. In addition to frame, we also manipulated and counterbalanced the future time (3, 4, or 12 months) and the fixed gift certificates amount ($50, $75, $100, and $115). The dependent variable for each titrator was each participant's exponential annual discount rate, δ, as implied by the midpoint between preferring the earlier versus later payments (i.e., the indifference point). Values of δ closer to one (larger) indicated less discounting and thus more patient preferences.

Loss aversion was also measured with five choice titrators (Fehr & Goette, 2007). Each titrator presented participants with a series of choices indicating willingness to play each of a series of binary gambles with a 50% chance of winning some fixed amount ($6 or $20) and a 50% chance of losing some varying amount (between $.50 to $7 in $.50 increments or between $2 to $24 in $2 increments). Two of the titrators in the first wave were repeated without change in the fourth wave one year later. We calculated loss aversion coefficients, λ, by dividing the gain amount by the loss amount at the indifferent point (i.e., midpoint between where the

participant switches from willing to play the gamble to not willing). Values of λ were reverse coded so that larger values indicated better *loss neutrality*.

Financial and debt literacy were measured using a single six-question scale composed of three financial literacy questions (Lusardi & Mitchell, 2006) designed to assess knowledge of fundamental economic concepts and three debt literacy questions (Lusardi & Tufano, 2009) designed to assess knowledge of compound interest and credit card debt (see Table S1).

Table S1. Financial and debt literacy questions.

FL1. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?
- − More than today
- − Exactly the same as today
- − Less than today
- − Do not know

FL2. Do you think that buying a single company stock usually provides a return that is more safe, equally safe, or less safe than the return on a stock mutual fund?
- − More safe return than a stock mutual fund
- − Equally safe return as a stock mutual fund
- − Less safe return than a stock mutual fund
- − Do not know

FL3. Is using money in a bank savings account to pay off credit card debt usually a good or a bad idea?
- − Good idea
- − Bad idea
- − Do not know

DL1. Suppose you owe $1000 on your credit card and the interest rate you are charged is 20% per year compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double?
- − 2 years
- − Less than 5 years
- − More than 5 but less than 10 years
- − More than 10 years
- − Do not know

DL2. You owe $3,000 on your credit card. You pay a minimum payment of $30 each month. At an Annual Percentage Rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new charges?
- − Less than 5 years
- − Between 5 and 10 years
- − Between 10 and 15 years
- − Never, you will continue to be in debt
- − Do not know

DL3. You purchase an appliance which costs $1,000. To pay for this appliance, you are given the following two options: a) pay 12 monthly installments of $100 each, b) borrow at a 20% annual interest rate and pay back $1,200 a year from now. Which is the more advantageous offer?
- − Option (A)

–   Option (B)   –   Do not know
–   They are the same

Resistance to anchors was measured with six numerical estimation questions (e.g., distance between New York and Cairo), four of which were accompanied by anchors. For each set of three questions, participants saw one question with a high anchor (e.g., 11300 miles), one with a low anchor (e.g., 1400 miles), and one with no anchor. Questions were counterbalanced with anchor condition. We calculated standardized estimates by pooling responses across high, low, and no anchor conditions within question. Thus, the four dependent variables were the z-scores for the two low-anchor questions and reverse-coded z-scores for the two high-anchor questions. Higher values on these measures correspond to less anchoring.

Resistance to framing was measured in four different scenarios that asked participants to choose between a risky option and a sure option and varied the framing of the options as losses or gains (Tversky & Kahneman, 1981). We used the classic Asian disease problem (e.g., number of lives saved or lost), as well as variants involving potential layoffs (e.g., number of factories kept open or shut down), drought (e.g., acres of crops saved or lost) and bankruptcy (e.g., invested money saved or lost). Each participant saw either the gain version or the loss version of each scenario. Gain scenarios offered a choice between a sure but partial gain (e.g., 100% chance that 200 lives will be saved) and a risky option with chances of full gain and no gain (e.g., 33% chance that 600 lives will be saved and 67% chance that 0 lives will be saved). Loss scenarios offered a choice between a sure but partial loss (e.g., 100% chance that 400 lives will be lost) and a risky option with chances of no loss and full loss (e.g., 33% chance that 0 lives will be lost and 67% chance that 600 lives will be lost). Because these framings provide identical choices, Expected Utility maximizers should choose the same option under either framing, but Prospect Theory predicts that people susceptible to the framing will choose the sure option in the gain frame and the risky option in the loss frame. Susceptibility to framing is thus a binary measure of

whether, for each pair of scenarios, choices follow consistent risk preferences regardless of framing (1 if either both risk-averse or both risk-seeking) or not (0).

1.2 Cognitive Measures

1.2.1 Fluid intelligence

Our most widely recognized measure of fluid intelligence is the *Raven's Progressive Matrices* task (Raven, 1962), a non-verbal test of inductive and analytic reasoning. The version we used, adapted from Salthouse, Pink and Tucker-Drop (2008) consisted of patterns in the form of 3x3 matrices with one cell missing. Participants had to determine the underlying rules that produce the pattern of rows and columns in the matrix which of the eight choice options correctly completed the pattern. Participants had 10 minutes to answer up to 18 matrices. Each item was presented on its own page and participants could choose to skip a question by selecting "no answer" but could not return to earlier items. Performance on this task was measured by the number of correct responses (0-18) with no penalty for incorrect responses.

Letter Sets (Ekstrom, French, Harman, & Dermen, 1976; Thurstone, 1962) is another measure of inductive and reasoning ability. The version of the task used in this study was also adapted from Salthouse et al. (2008). In this task, participants were presented with five sets of letters (e.g., NOPQ, DEFL, ABCD, HIJK, and UVWX) and they had to find the rule that related four of the five sets by checking the one which did not fit that rule (e.g., DEFL). Participants had 10 minutes to complete up to 15 items. As with the Raven Progressive Matrices, each item was presented on its own page and a "no answer" option allowed participants to skip items. The score for this task was calculated by the number of correct responses with no penalty for incorrect responses.

Number Series (Thurstone, 1962) is yet another measure of inductive and reasoning ability with particular emphasis on quantitative reasoning. The version we have used in this study is a block adaptive test developed by (McArdle & Woodcock, 2009) for the HRS 2010. Each item consisted of a series of numbers (e.g., 23, 26, 30, 35, __), and participants identified

the number that correctly completed the series. All participants saw the same three items in the first block. The number of items answered correctly determined the difficulty of the three items in a second block. Thus, each participant completed six items in total, and a Rasch score was calculated based on which second block the participant completed and how many answers they got right in each block.

The *Cognitive Reflection Test* (CRT; Frederick, 2005; Frederick, Loewenstein, & O'Donoghue, 2002) consists of three mathematical questions that yield quick, impulsive, but incorrect first responses, which need to be inhibited to arrive at the correct answer. According to Frederick, the *"three items on the CRT are 'easy' in the sense that their solution is easily understood when explained, yet reaching the correct answer often requires the suppression of an erroneous answer that springs 'impulsively' to mind"* (Frederick, 2005, p. 27). The dependent variable used is the number of correct responses (0-3) with no penalty for incorrect responses.

Numeracy (Lipkus, Samsa, & Rimer, 2001) is the ability to understand probability and mathematical concepts. The numeracy task we used in our study consists of 11 questions that test comprehension and manipulation of proportions, percentages, and probabilities. The dependent variable used is the number of correct responses (0-11) with no penalty for incorrect responses.

1.2.2 Crystallized intelligence

Shipley's vocabulary (Zachary, 1986) is a synonym vocabulary task that measures vocabulary knowledge. In our version, adapted from CREATE's Common Core Battery of Measures (Czaja, Charness, Dijkstra, et al., 2006; Czaja, Charness, Fisk, et al., 2006), participants choose from among four words the one most similar in meaning to a target word. Participants had 10 minutes to complete up to 40 items split into two screens of 20 items each. In this task, a visible timer counted down on the upper left hand corner of the computer screen. The dependent measure used for this task is the number of correct responses (0-40) with no penalty for incorrect responses.

Antonym vocabulary also measures vocabulary knowledge, using items developed by

Salthouse (1993). In contrast to the Shipley's synonym vocabulary however, in this task participants choose from among five words the one most nearly opposite in meaning to a target word. Participants had five minutes to complete up to ten items, with a visible timer. Each item was presented on its own page but participants could choose to skip an item by selecting "no answer". Their score was the number of correct responses (0-10) with no penalty for incorrect responses.

The *Information* task (WAIS-III) (Wechsler, 1997) also adapted from CREATE (Czaja, Charness, Dijkstra, et al., 2006; Czaja, Charness, Fisk, et al., 2006) consisted of questions that measure general factual knowledge about events, objects, places, and people. Online administration required participants to read the questions on the computer screen and type their responses rather than having the questions read to them by a tester and answering verbally. We used the acceptable responses for each item as listed in the CREATE manual (Czaja, Charness, Dijkstra, et al., 2006) to determine whether an answer is correct. Because we could not prompt participants to give further details for a question, we could only code answers as correct (1) or incorrect (0) (instead of the original 0, 1, 2 scoring). Participants answered 28 questions without time restriction. The dependent measure used for this task is the number of correct responses (0-28) with no penalty for incorrect responses.

REFERENCES

Czaja, S. J., Charness, N., Dijkstra, K., Fisk, A. D., Rogers, W. A., & Sharit, J. (2006). CREATE common core battery of measures: Technical report No. CREATE-2006-01. Atlanta, GA: Center for Research and Education on Aging and Technology Enhancement (CREATE).

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging, 21*(2), 333-352.

Ekstrom, R. B., French, J. W., Harman, H. H., & Dermen, D. (1976). *Manual for kit of factor-referenced cognitive tests*. Princeton, NJ: Educational Testing Service.

Fehr, E., & Goette, L. (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *American Economic Review, 97*(1), 298-317.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives, 19*(4), 25-42.

Frederick, S., Loewenstein, G., & O'Donoghue, T. (2002). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature, 40*(2), 351-401.

Green, L., Fry, A. F., & Myerson, J. (1994). Discounting of delayed rewards: A life-span comparison. *Psychological Science*(5), 33-36.

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General Performance on a Numeracy Scale among Highly Educated Samples. *Medical Decision Making, 21*, 37-44.

Lusardi, A., & Mitchell, O. S. (2006). *Financial Literacy and Planning: Implications for Retirement Wellbeing*. Pension Research Council. Wharton School, University of Pennsylvania.

Lusardi, A., & Tufano, P. (2009). *Debt Literacy, Financial Experiences, and Overindebtedness*. Retrieved from http://www.dartmouth.edu/~alusardi/Papers/Lusardi_Tufano.pdf

McArdle, J. J., & Woodcock, R. W. (2009). *Adaptive testing with selected Woodcock cognitive tests*. Longitudinal Research Institute. Charlottesville, VA.

Raven, J. (1962). *Advanced Progressive Matrices, Set II*. London: H. K. Lewis.

Salthouse, T. A. (1993). Speed mediation of adult age differences in cognition *Developmental Psychology, 29*, 722-738.

Salthouse, T. A., Pink, J. E., & Tucker-Drop, E. M. (2008). Contextual analysis of fluid intelligence. *Intelligence, 36*, 464-486.

Thurstone, T. G. (1962). *Primary mental ability for Grades 9-12 (Rev. ed.)*. Chicago, IL: Science Research Associates.

Wechsler, D. (1997). *Wechsler Adult Intelligence Scale III (3rd ed.)*. San Antonio, TX: The Psychological Corporation.

Zachary, R. A. (1986). *Shipley Institute of Living Scale: Revised manual*. Los Angeles: Western Psychological Services.