Temporal Instability of Risk Preference among the Poor: Evidence from Payday Cycles*

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Abstract

The poor live paycheck to paycheck and are exposed to strong cyclical income fluctuations. We investigate whether such income fluctuations affect individuals' risk preference. If risk preference temporarily changes around payday, the optimal decisions made before the payday may no longer be optimal after the payday, which could be another source for the poverty trap. By exploiting the payday cycles of Social Security in the US, we find that risk preference of the poor who heavily relies on Social Security changes around payday. We find suggestive evidence that the deterioration of mental health rather than cognitive decline before payday may play a role. Similar evidence among the Japanese elderly is obtained.

Keywords: poverty, risk preference, Social Security, mental health, cognitive function, elderly, Health and Retirement Survey, Japanese Study of Aging and Retirement
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1. Introduction

The poor often live paycheck to paycheck, and heavily relies on the government transfer payment from pension and social welfare programs. Numerous studies have documented that consumption indeed increases sharply after the recipient of such payment, suggesting that individuals lack financial resources before payday.[1] Since these payments are usually periodic (e.g., paid monthly), the poor are more likely to be repeatedly exposed to strong and nearly unavoidable cyclical income fluctuations.

This paper asks whether such *frequent*, *temporary*, and *anticipated* income fluctuations—induced by periodic payments—alter individuals' risk preference. Risk preference is the fundamental determinant of individuals' economic decision-making regarding ordinary issues (e.g., payday loan, and purchase of lottery tickets) as well as issues with long-term consequences (e.g., saving, investment, and insurance choices). As a result, the temporal change in risk preference around payday—if it exists—indicates that the optimal decisions involving risk and uncertainty made before the payday may no longer be optimal after the payday at a different level of risk preference (Andersen et al. 2008; Harrison et al. 2020).[2] If such non-optimal decisions further deepen the poor's dependence on periodically paid welfare programs, such time-varying risk preference induced by periodic payment may be another source for the feedback loop that contributes to the poverty trap. Since periodic payment of pension, salaries, and social welfare programs (e.g., Supplemental Nutrition Assistance Program, and Supplemental Security Income in the US) is ubiquitous around the world, the answers to this universal question can have substantial policy relevance.

We test this question by exploiting payday cycles of Social Security in the US. In our sample period, Social Security benefits are paid on the 3rd of the month.[3] Past literature documented that expenditures (Stephens 2003), food consumption (Mastrobuoni and Weinberg 2009), and caloric intakes (Shapiro 2005) increase sharply on the 3rd of the month, indicating that individuals run out of disposal income before payday. Since the restricted version of Health and

[1] See, for example, studies in the US (Stephens 2003; Shapiro 2005; Mastrobuoni and Weinberg 2009) and in the UK (Huffman and Barenstein 2005; Stephens 2006).
[2] Harrison and Ng (2016) show that the welfare of social insurance policy is contingent on the risk preferences of the beneficiaries. If the risk preference is unstable over time, what we consider as a welfare-enhancing policy today could become a welfare-reducing policy in the future (Harrison et al. 2020).
[3] If the third day of the month falls on a weekend or holiday, benefits are paid on the first business day before the third.

Retirement Study (HRS)—the working data in this study—includes the exact interview dates, we can compare the risk preference of those who are interviewed before the Social Security payday (i.e., 3rd of the month) and those who are interviewed after the Social Security payday. We run balanced tests to ensure the random assignment of interview dates to subjects over the month. This approach allows us to obtain the causal estimate of the effect of income fluctuation around payday on risk preference of Social Security beneficiaries.[4]

We find that risk preference—measured by the hypothetical gambles over *lifetime* income in HRS—change around payday among beneficiaries of Social Security. In particular, the individuals, who heavily rely on Social Security income and are indeed poor (average annual household income is USD 24,688), become *more* risk tolerant just before payday—when financial resources are scarce—than after payday.[5] In terms of the magnitude, the risk tolerance parameter is 50% higher before payday than the mean of the outcome, which cannot be dismissed just as meaningless noise. We do not find the same systematic pattern for those who are relatively richer and as a result do not heavily rely on Social Security income, suggesting that the Social Security income plays a role.

Our results are robust to different ways of defining heavy dependence on Social Security income, different ways of constructing outcomes, and different specifications. Furthermore, our results are more pronounced among households that have little savings who are especially illiquid in the days leading up to the payday. Taken together, these results suggest that the risk preference of the poor elderly who heavily rely on Social Security payment may not be temporally stable in the short intervals at least in our setting.

To probe the mechanisms of the temporal change in risk preference, we first examine the cognitive functions around the payday. Mullainathan, Shafir, and their coauthors argue that financial strain impedes cognitive function and worsens the quality of decision-making.[6] We do

[4] Whereas our *across*-subjects design does not allow us to compare the level or rank stability of risk preference within the same individuals (*within*-subjects), this approach still enables us to compare the *aggregate* of risk preference and obtain the causal estimates of temporal financial shocks on risk preference. Mastrobuoni and Weinberg (2009) also take a similar approach of across-subjects design which exploit random interview dates around Social Security payday.

[5] One might be concerned that this result does not reflect the change in risk preferences per se but the liquidity constraints restrict the choices of individuals (Haushofer and Fehr 2014). However, if individuals choose the safe option to alleviate liquidity constraints, it goes against our finding. Also, our risk preference is measured by the choice of lifetime income instead of immediate payment, which also mitigates such a concern.

[6] Shah et al. (2012), Mullainathan and Shafir (2013), and Mani et al. (2013). See also Schilbach et al. (2016) and Dean et al. (2019).

not find any before-after payday difference in cognition measures, implying that the cognitive decline around payday does not seem to explain the temporal shift in risk preference. Instead, we find suggestive evidence that mental state plays some role. We find that individuals are more likely to be depressed before payday than after payday. Since we do not observe any changes in mental health among individuals who do not heavily rely on the Social Security income, the deterioration of mental health before payday might be one channel through which risk preference changes around the payday.

To assess external relevance, we also examine the same question using the data for the elderly in Japan. This exercise is more than a simple replication in other countries since the US and Japan have very different baseline risk preference; the global survey on preferences by Falk et al. (2018) shows that Japan is one of the most risk-averse countries whereas the US is the opposite (see Figure 1 in Falk et al. 2018). Furthermore, the public pension in Japan is paid on the 15th of every *even* month instead of every month like in the US. This two-month interval between paydays allows us to include the week-of-the-month fixed effects (e.g., the effect of the first week of the month), which is impossible in the case of the US. This setting mitigates the concern that results in the US are driven by other events at the beginning of the calendar month such as housing payment.[7] We find collaborative evidence that is consistent with the results found in HRS data; individuals in Japan also become more risk tolerant just before payday than after payday.

This paper is at least related to two strands of the literature. First, this paper adds a new insight to the literature on the poverty and individual preferences. This literature argues that the economic environment of the poor shapes one's individual preference.[8] We propose a new contextual feature—time-varying risk preferences induced by the periodic payments—which might lead to suboptimal decisions, as another potential trigger that reinforces poverty. Our results provide the case for the consumer protection laws such as the cooling-off period for contracts to cancel a purchase (Rekaiti and Van den Bergh 2000; Schildberg-Hörisch 2018). In addition, one potential solution to mitigate the temporal shift in risk preference may increase the

[7] For example, Vellekoop (2018) shows that most of the housing payments (either rent or mortgage payments) are concentrated at the beginning and the end of the calendar month in the US.

[8] None of the studies explicitly focus on the elderly. See, for example, Lawrance (1991), Banerjee and Mullainathan (2010), Tanaka et al. (2010), Spears (2011), Gloede et al. (2015), Carvalho et al. (2016), Bartos et al. (2018), and Haushofer and Fehr (2019).

frequency of payments and shorten the intervals between the payments. More frequent access to income allows people to smooth consumption (Stephens and Unayama 2011), and potentially mitigates the financial distress.[9]

Second, this paper is related to more broad literature on the stability of preferences.[10] Preferences are generally assumed to be static economic primitives, which are stable over time (Stigler and Becker 1977). The growing literature investigates whether large one-time, permanent and unanticipated financial shocks like Great Depression shift *baseline* risk preference (e.g., Necker and Ziegelmeyer 2016; Guiso et al. 2018).[11] Instead, we evaluate the impact of the frequent, temporal, and anticipated variation in financial resources with modest size on the *temporal* shift around baseline risk preference (Schildberg-Hörisch 2018).[12] The payment is frequent (i.e., every month), and anticipated since the beneficiaries of Social Security know the exact payday and the amount of payment. We show that even commonly occurring income fluctuation of realistic magnitude might temporarily alter the risk preference of the individuals.[13]

The rest of the paper is organized as follows. Section 2 describes the data, and Section 3 presents our identification strategy. Section 4 reports our findings from HRS, and Section 5 reports the supplemental findings from Japanese data. Section 6 concludes.

2. Data

2.1. Sample selection

Our dataset is the Health and Retirement Study (HRS)—the nationally representative

[9] For example, the pension is paid every two weeks in Australia.
[10] For risk preferences, see Mata et al. (2018) for review. For time preferences, see Krupka and Stephens (2013), and Meier and Sprenger (2015). For social preferences, see Carlsson et al. (2014), and Volk et al. (2012).
[11] A growing literature has suggested that experiencing not only financial crises but other large negative shocks such as natural catastrophes, and conflicts may alter one's risk preference. See Chuang and Schechter (2015), and Schildberg-Hörisch (2018) for a review.
[12] Schildberg-Hörisch (2018) provides the conceptual framework to distinguish between permanent and temporal shifts in risk preferences throughout the life course.
[13] Alternatively, our results can be interpreted as the state-dependent preferences where preferences are a stable function of states of nature that change over time (i.e., income), as long as these states are exogenous. This would allow choices to vary with various states of nature keeping the preference to be stable. However, it is empirically challenging to answer what constitutes an appropriate "state of nature" (Andersen et al. 2008; Dasgupta et al. 2017).

survey for the elderly in the US—collected biannually. We use data from 1994, 1998, 2000, 2002, and 2006.[14] The restricted version contains the exact interview dates, which are crucial information for our empirical strategy.

The HRS is randomly administered by the Survey Research Center at the University of Michigan to individuals over the month. During the time period covered by our data, Social Security benefits were paid out on the 3rd of the month unless that date was a holiday or on the weekend, and, if so, on the first business day prior to the 3rd of the month. Between 1994 and 2006, 73.1% of Social Security beneficiaries received their checks through direct deposit, and thus have access to their benefits on pay dates (Social Security Administration 2019).

Using the information on the exact interview date, together with known Social Security payday, we can calculate the distance in days between the interview date and Social Security payment day.[15] Then, we use the distance (in days or weeks) as the proxy variable for the respondent's financial resources. This approach enables us to compare the individual preferences of those who are interviewed before the Social Security payment (i.e., who are more likely to run out of money) and interviewed after the Social Security payment (i.e., who are more likely to have sufficient financial resources). In Section 3.2, we show that the interview dates are randomly assigned to individuals, and thus are uncorrelated with the date on which individuals receive their Social Security paycheck.

We restrict our sample to single or coupled households with at least one member over 62 starting to receive Social Security payment before May 1997.[16] Following Mastrobuoni and Weinberg (2010), we drop the widowed and divorced from the sample to ensure that an individual is not paid based on an ex- or deceased spouse's payment schedule. We then also drop household with at least one member receiving Supplemental Security Income (SSI) which follow different payday cycles.

Individuals from low-income households are unavoidably more dependent on Social

[14] Whereas HRS initiated in 1992, we did not include 1992 because there are only four risk categories in 1992 in the hypothetical gamble question, that we use to derive the risk preference parameter. It was expanded to 6 categories from 1994 onwards. The hypothetical gamble question is no longer asked after 2006. Note that the gamble question is asked to only new respondents and a random subsample of returning respondents. After the sample restriction imposed as detailed below, no observations are left in 2004.

[15] We verify with the HRS team that 92.4% of completed respondents start and end on the same date, so the measurement errors from the difference in interview dates and reply dates are minimal.

[16] For those who started receiving Social Security payments after May 1997, the payday changes to second, third, and fourth Wednesdays depending on the beneficiaries' birthday.

Security payment, and as a result, are more likely to be repeatedly exposed to cyclical income fluctuations. Appendix Figure A1 shows that individuals who have a high dependence on Social Security income are indeed poor. The figure plots the relationship between the share of Social Security income among total household income on the x-axis and the total household income on the y-axis. It clearly shows that high dependence on Social Security is driven by low total household income (i.e., the denominator of the share) since the amount of Social Security (i.e., the numerator of the share) does not vary much across individuals. For that reason, we divide the sample by the individuals from households in which the share of Social Security income among total household income is above (more reliant and poor/low-income) or below (less reliant and rich/high-income) the sample median, which corresponds to an income share of at least 44%.[17] Similar approaches are taken by Stephens (2003), and Mastrobuoni and Weinberg (2009). Later, we show that our results are qualitatively robust to changing the thresholds to 40, 50, and 60% share of Social Security income to define high/low dependence.

2.2. Outcome: Risk tolerance

Here, we describe how our risk preference is measured and constructed. The HRS uses hypothetical gambles over lifetime income to elicit risk attitudes. Respondents choose between a safe job and a risky job in hypothetical scenarios. With equal chances, a risky job will double the income or cut monthly income by a specific fraction. Varying the size of downside risk on the monthly income in subsequent questions refines the measure of risk preference. See Appendix Table C1 for the exact wording in the questionnaires.

We follow Barsky et al. (1997) and Kimball et al. (2008) to derive the risk tolerance parameter θ for each individual. Specifically, we assume that constant relative risk aversion (CRRA), $U(W) = \frac{W^{1-1/\theta}}{(1-1/\theta)}$, well approximates individuals' utility over lifetime income, and that the coefficient of relative risk tolerance $\theta = -U'/wU''$ may differ across individuals (Pratt 1964). Appendix Table A1 provides the relationship between the six gamble response categories and the

[17] Whereas Mastrobuoni and Weinberg (2009) limit their sample to individuals from households in which Social Security income makes up at least 80 % of total household income, the fraction of those individuals in their sample is 41%, which is roughly similar to our sample share above the sample median. When we apply this more stringent 80 percent criteria to our sample, the fraction of those individuals in our sample is only 13.82% (N=166). This indicates that our sample is relatively less reliant on Social Security income than that of Mastrobuoni and Weinberg (2009) using Continuing Survey of Food Intake by Individuals, 1994–1996.

corresponding downside risks that the individual accepts and rejects.[18] We later show that our results are also robust using the ordinal measure of risk tolerance in Section 4.2.

Panel (a) of Appendix Figure A2 shows the frequency distributions of gamble responses. The figure reveals substantial heterogeneity in risk attitudes. The figure also shows that most individuals are unwilling to take risks and roughly half of the respondents belong to the lowest risk category (category 1).

Even though the gamble response is hypothetical, there are three main reasons to justify the use of this variable to examine the stability of risk preference (Camerer and Hogarth 1999). First, Barsky et al. (1997) show that this risk measure obtained by hypothetical gamble questions in HRS is correlated with actual risk-taking behaviors such as smoking, drinking, and ownership of financial assets. Second, the stakes of the gambles over lifetime income are large which is necessary to properly measure risk preference within the expected-utility framework, as discussed in Rabin (2000). Finally, Dohmen et al. (2011) validate the use of hypothetical choice data by using incentivized lottery questions. In fact, this risk tolerance measure in HRS is widely used in previous studies (e.g., Barsky et al. 1997; Kimball et al. 2008; Sahm 2012). Despite some limitations, the risk preference parameter using gamble responses on lifetime income offer valuable information on the magnitude and sources of change in risk preference (Sahm 2012).

Table 1 presents descriptive statistics for the analysis sample. The first row in Table 1 shows that the mean of the risk tolerance parameter in the sample is 0.555 with a standard deviation of 0.848. The average age is 69.2 years, and 91% of the sample is married. Roughly half (48.4%) are female.

3. Identification strategy

3.1. Econometric model

We first organize the interview dates in relation to the 3rd of each month. For ease of explanation, we use the 3rd of the month, but it is adjusted by a few days if the 3rd of the month is not a weekday. Then, we construct each synthetic month around the 3rd of the month ranging

[18] The category numbers are higher as the individual's willingness to accept income risk increases, and thus the corresponding risk tolerance parameter is larger. We use the midpoint of the intervals of risk tolerance parameters between the two adjacent risk categories. As a robustness check, we construct an ordinal risk tolerance measure that does not rely on the interval of the risk categories as described in Section 4.2.

from –14 to +13, and limit the sample to 14 days around the payday (Stephens 2003). Importantly, we can *exactly* identify before and after payday without errors as we know both the exact payday as well as the interview day.[19]

Given this structure of the data, the econometric model is written as

$$Y_i = \sum_{k\neq+1}^{k=-1,-2,+2} \beta_k 1(week = k) + \gamma X_i' + \delta_{FE} + \varepsilon_i, \quad [1]$$

where Y_i is the outcome for individual i. $1(week = k)$ is a dummy that takes one if the week belongs to two weeks before ($k = -2$), a week before ($k = -1$), and two weeks after ($k = +2$) the payday (Stephens 2003, 2006; Evans and Moore 2011, 2012). We later show that our results are robust to narrowing the sample just around the payday and using the daily interval instead of week aggregation which gives more statistical power. Our reference week is a week right after the payday ($k = +1$). Since we are particularly interested in the effect of financial strain on risk preference, our main coefficient of interest is β_{-1}, a coefficient on a week *before* the payday. This coefficient captures before-after payday difference in outcomes. The estimates on other week dummies help us understand the within-month dynamics of change in outcomes in the long spell, which is not possible with only one-week interval data (cf. Carvalho et al. 2016). X_i' are the individual characteristics, namely age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies. We also include a number of fixed effects, δ_{FE}, namely day of the week FEs, year FEs, month FEs, and year-month FEs. ε_i is an error term. We estimate an equation [1] by OLS unless specified otherwise.

The change in financial resources around payday could affect one's risk preference in two opposite ways. On one hand, limited financial resources before payday could increase the marginal utility of consumption, and hence reduce one's willingness to take risks. This observation is in line with association studies showing that the poor tend to be risk averse (Guiso and Paiella 2008; Dohmen et al 2011). On the other hand, the literature on social comparison argues that relative deprivation compared with others tends to increase ones' willingness to take risks, as individuals strive to catch up to their comparison standards (Mishra et al. 2015; Payne et al. 2017). For example, Haisley et al. (2008) show that increased feelings of poverty among low-income individuals induce peoples to take more risks (buying more lottery tickets) to correct for

[19] This setting allows us to avoid the potential endogeneity of the survey response timing in Carvalho et al. (2016). See Mani et al. (2020) for further discussion on this point.

their low-income status. Relatedly, Risk Sensitive Theory (RST) suggests that individuals shift from risk-aversion to risk-proneness in situations of higher perceived need, where need refers to a disparity between an individual's present state and the desired state (Pietras and Hackenberc 2001; Mishra and Lalumière 2010).[20] If a lack of financial resources before payday increases ones' feelings of poverty against others or ones' desired state, one might be more willing to take risks. Finally, as we discuss in Section 4.3, the empirical evidence of stress/depression associated with financial worries on risk preference is very mixed. Therefore, we view that the direction of change in risk preference at payday is ultimately an empirical question.

3.2.Randomization tests

The key to our identification strategy is that the interview dates are randomly assigned to individuals, and thus are uncorrelated with the date on which individuals receive their Social Security paycheck. To test that the interview dates are exogenous to financial constraints, following Mastrobuoni and Weinberg (2009), we estimate an equation [1] where outcomes are predetermined variables in the dataset. We test for differences in weeks in the pay period, separately for age, gender, years of schooling, and an indicator for married, retired, in good health, in poor health, and black. We also test for differences in indicators for whether a household is located in the Northeast, Midwest, South, or West.

Table 2 presents the results of the randomization tests for the entire sample in panel (a), and separately for individuals from households in which the share of Social Security income among total household income is above the sample median in panel (b), and below the sample median in panel (c). The table presents F-tests of the joint null hypothesis that each of the estimates on the four-week dummies is equal to zero with corresponding p-values. Table 2 shows that only regional dummies are sometimes statistically different at the 5% levels, potentially reflecting that the survey was administered at different times for each region. In our regressions, we control for all these predetermined variables.[21]

[20] This theory from biology is originally developed to explain animal foraging behaviors. See Mishra (2014) for a review.

[21] One remaining issue is the sample selection: it could be problematic if individuals with higher or lower risk tolerance are symmetrically more likely to select into the survey in a particular week. Whereas testing the issue of sample selection requires risk tolerance measures on respondents who are not interviewed (which do not exist), it is reassuring that at least observable characteristics among those who are interviewed are balanced. See Harrison et al. (2020) for discussions on endogenous sample selection and attrition.

4. Results

4.1. Graphical evidence

We first present our graphical evidence. Figure 1 plots the measures of risk tolerance θ, for individuals for whom the share of Social Security income is above the sample median in panel (a) and below the median in panel (b), with 2-day bins around the payday. Panel (a) clearly shows that the risk tolerance parameter is discontinuously higher just before the payday, indicating that respondents are *more* risk tolerant just before payday. Interestingly, within the course of the month, the risk tolerance parameter is monotonically increasing, indicating that respondents gradually become more risk tolerant as they become more financially distressed. On the contrary, we do not see such a systematic pattern for below-median respondents in panel (b), suggesting that the results for the above-median respondents are indeed driven by the availability of Social Security income.

4.2. Basic results

Here, we formally present the results from estimating an equation [1]. The results are shown in Table 3. Column (1) of Table 3 shows the estimate for the respondents with high dependence on Social Security income (i.e., above sample median). Before payday week ($k = -1$) is associated with the increase of risk tolerance by 0.287. Since the mean of the risk tolerance parameter is 0.516 in this sample, this represents a 55.6% increase in risk tolerance from the mean. Other week dummies are not statistically significant at conventional levels. On the contrary, column (2) of Table 3 shows no such a pattern among the respondents who rely less on Social Security income. Taken together, these results indicate that payment of Social Security plays a role in elevated risk tolerance before payday.

Robustness—. Our results on risk tolerance are robust to different ways of defining high dependence on Social Security income. Table 4 presents the results where we define the high dependence by 40, 50, and 60% of the share of Social Security income among total household income, which corresponds to 55, 41, and 29% share of the overall sample.

For ease of comparison, column (1) in Table 4 replicates the baseline estimates from column (1) from Table 3, where we define high dependence by the sample median (income share

is 44%, N= 602). When we define high dependence by 40% and 50% in the share of Social Security income, the estimates on a week before payday stay statistically significant at the 5% level. Whereas we lose the statistical significance to a 10% level, once we change the threshold to 60% (N= 346), the estimate on a week before payday is similar to the baseline specification in column (1). Appendix Table A2 reports the results for those below the 40, 50, and 60% thresholds, and find no changes in risk preference before payday, reassuring our null-effect for those who rely less on Social Security income.

Our results are not driven by the cardinality of our risk preference measure. We instead construct an ordinal measure which takes one if respondents choose the most and second most risk-tolerant categories (categories 5 and 6) in the gamble question, or zero otherwise. Column (1) of Appendix Table A3 shows that our results are robust using this ordinal measure. Column (2) reports the estimates of the ordered Probit model, and our results are again robust to different specifications.

Finally, we estimate the regression discontinuity (RD) model as a part of our robustness check, using the distance from the payday (measured in days) as a running variable.[22] Appendix Table A4 summarizes the results. It is rather surprising that we obtain statistically significant results ($p<0.01$), even with this small sample size. Since we only use the sample in the vicinity of the payday, the RD estimates are larger than our baseline OLS estimates. We prefer our OLS approach over RD design because we are not only interested just a day apart from the payday, but the entire profile of the risk tolerance parameter throughout the month. In addition, the sample size is quite small for RD to conduct a heterogeneous analysis below. Nonetheless, it is reassuring that our results are robust to this different specification.

Heterogeneity—. We further examine whether the effect is more pronounced among respondents for whom we expect larger responses. To this end, we split the sample above the median to non-savers and savers, where savings are defined as the net value of all savings worth at least $10000.[23] We expect the effect size to be larger for non-savers as he or she is especially illiquid in the days leading up to the Social Security payday. Table 5 confirms this conjecture. We find that non-savers are more likely to become more risk tolerant before the payday in

[22] We follow Calonico et al. (2014) to choose the data-driven optimal bandwidth.
[23] More precisely, a saver is defined as an individual who holds the net value of stocks, mutual funds, and investment trusts, the value of checking, savings, or money market accounts, the value of CD, government savings bonds, and T-bills, the net value of all other savings worth at least $10000.

column (1). The estimate of 0.403 ($p<0.05$) translates into a roughly 82% increase in risk tolerance measure from the mean. By contrast, we do not observe the same pattern for savers in column (2). Given the small sample size, the estimates on a week before payday between non-savers and savers are statistically indistinguishable at the conventional level ($p= 0.339$). Appendix Table A5 repeats the same exercises for the sample of individuals whose share of Social Security among total household income is above 40, 50, and 60%, and find qualitatively similar patterns for both non-savers and savers.

Placebo—. We run the same specification for the samples that we do not expect to find effects. Appendix Table A6 reports the results. In particular, we examine two samples: (i) people aged 50-61 years who are younger than the eligibility age of 62 for Social Security, and (ii) people aged 62 and over who do not yet receive Social Security income. It is reassuring that none of the estimates on the week before payday are statistically significant nor economically large.

4.3. Possible Mechanism

Thus far, we provide robust evidence that the individuals become more risk tolerant just before payday among individuals from households that have a heavy dependence on Social Security income. To probe the mechanism, we examine the cognitive function as well as the mental health of beneficiaries before and after the payday.

Cognitive function—. A number of studies present the link between cognition and risk preference (e.g., Frederick 2005; Burks et al. 2009; Dohmen et al. 2010; Benjamin et al. 2013). More recently, Mullainathan, Shafir, and their coauthors argue that poverty reduces cognitive capacity because poverty-related concerns consume mental resources (called bandwidth), degrading also the quality of decision-making. In particular, Mani et al. (2013) find that the cognitive function of farmers in India diminishes before harvest, when poor, as compared with after harvest, when rich. On the contrary, Carvalho et al. (2016) do not find supportive evidence that financial strain impedes cognitive function and worsens the quality of decision-making.

Interestingly, Lichand and Mani (2019) argue that the discrepancy between Mani et al. (2013) and Carvalho et al. (2016) can be explained by (i) the lack of uncertainty in payment timing and amounts in Carvalho et al. (2016), and/or (ii) higher income levels of the US respondents, relative to Indian farmers in Mani et al. (2013). Since the timing and amount of Social Security are known to the beneficiaries, the lack of cognitive decline in our case could be

also explained by the lack of uncertainty.

Following Ayyagari and Frisvold (2016), we define the cognition status based on a 27-point score composed of the word recall, serial 7s, and backward counting tests. Panel (b) of Appendix Figure A2 shows the distributions of a 27-point cognition score. Scores between 12 and 27 are classified as normal, between 7 and 11 as cognitively impaired but not demented (CIND), and between 0 and 6 as demented. Among the households whose income share of Social Security is above the sample median, the fractions of CIND and demented are 18.3%, and 3.2% respectively (see Table 6).

Table 6 reports the estimates from an equation [1], where the outcome is a dummy for being normal, CIND, and demented in each column. None of the estimates in Table 6 are statistically significant at the conventional levels. Appendix Table A7 repeats the same exercises for the sample of individuals whose share of Social Security among total household income is above 40, 50, and 60%, and do not find any before-after payday changes in any outcomes. Thus, the cognitive load does not seem to drive our results, at least in our setting and within our measures of cognitive function (cf., Raven's Matrices test).

Mental status—. Next, we look at the mental status or mood. Mental health could be susceptible to income fluctuation as financial strain is often associated with higher levels of stress and depression (see Haushofer and Fehr 2014, and Ridley et al. 2020 for a review).[24] The empirical evidence of stress/depression on risk preferences is, however, mixed at best (Kremer et al. 2019).[25] The evidence from these studies is less informative for our setting because most of them are conducted in the lab, and most importantly, examine the effect of one-time acute stress rather than moderate, temporary, and repeated stress like ours. Note that cognitive function and mental status are of course not mutually exclusive. Depressed individuals might be more likely to be cognitively impaired or vice versa.

HRS asks a question about depression. Specifically, it asks whether the person felt

[24] The psychology literature emphasizes that psychological well-being affects individuals' risk preferences (see Lerner et al. 2015 for a review).

[25] Some studies find that stress increases risk aversion (Mather et a. 2009; Porcelli and Delgado 2009; Kandasamy et al. 2014; Cahlíková and Cingl 2017), whereas others find it increases risk tolerance (Starcke et al., 2008; Putman et al., 2010; Pabst et al. 2013a, 2013b; Buckert et al. 2014; Cueva et al. 2015; Bayer et al. 2019) or has no significant effect (Delany et al. 2014; Sokol-Hessner et al. 2016). Cobb-Clark et al. (2020) do not find any differences in behavioral risk preferences between the mentally well and the depressed but they also find that depression is related to people's stated risk preferences and risk-taking behaviors which are context-specific.

depressed much of the time during the past week, and the respondent answers "yes/no." We create a dummy that takes the value of one if the person chooses "yes". Since the reference period of this question is a week from the survey date, we subtract seven days from the original distance in days and reconstruct the week dummies in an equation [1] accordingly.

Table 7 presents the results of depression. Column (1) in panel (a) presents the estimates from OLS for individuals whose Social Security share is above the sample median. The individuals who are heavily reliant on Social Security are 6.6% more likely to feel depressed a week before payday than a week after the payday ($p<0.10$). Since the mean is only 14.1%, we also report the estimates from the non-linear model, namely, probit (column (2)), and logit (column (3)).[26] The marginal effects of these non-linear models also show similar results with more precision in logit ($p<0.05$). Panel (a) of Appendix Table A8 repeats the same exercises for the sample of individuals whose share of Social Security among total household income is above 40, 50, and 60%, and again find that those who heavily rely on Social Security have a higher chance of suffering from depression before payday. The biggest impact is observed when the income share is set above the 60% threshold.

To examine whether mental health is the driving factor, we also examine the mental health of those who should not be much affected: those whose income share of Social Security is below the sample median. Panel (b) of Table 7 shows that those who rely less on Social Security are not depressed before payday. Panel (b) of Appendix Table A8 repeats the same exercises for the below 40, 50, and 60%–samples, and does not find any before-after payday difference on depression. Taken together, whereas it is at best suggestive, these contrasting results between high vs. low dependence imply that one of the many underlying mechanisms (e.g., self-control, emotions) for the increased risk tolerance before payday may be the deterioration of mental status. Importantly, whereas the question on depression in HRS refers to the past week from the interview date, risk tolerance is measured on the interview date; as a result, the respondents who answered each question are off by one week. This, unfortunately, precludes us from conducting a mediation analysis in our across-subjects design to examine whether depression is the underlying mediator for changes in risk preference.

Our results on risk preference differ from the seminal work by Carvalho et al. (2016)

[26] WHO (2017) in "Mental health of older adults" documents that approximately 15% of adults aged 60 and over suffer from a mental disorder, which is close to 14.1% in our data.

which also exploits randomness in survey dates and compares preference, cognitive functions, and decision-making shortly before and after payday among the US low-income respondents. They find that whereas the poor with liquidity constraints behave as if they are present biased before payday, they did not find any before-after differences in risk preference and the performance in cognitive function. Whereas the sign of their estimates on the CRRA parameter was indeed the same as ours (see Table 4 in Carvalho et al. 2016), their estimate was far from statistically significant.

The key advantage in our setting is that our nationally representative sample—albeit only elderly—includes both rich respondents who rely less on Social Security, as well as poor respondents who inevitably have to rely more, unlike Carvalho et al. (2016) which exclusively focuses on the poor.[27] The contrasting results on depression between the respondents with high vs. low dependence on Social Security imply that mental health seems to play some role. While this is at best speculative and identifying the underlying mechanism is beyond the scope of this paper, the depressed mood before payday—potentially due to increased feeling of poverty against others or ones' desired state—could be one potential reason for the difference between Carvalho et al. (2016) and our study.[28] Relatedly, another potential reason is that we exclusively focus on the elderly; the elderly could be more mentally vulnerable, and sensitive to even temporary and anticipated income fluctuation.[29,30] In this regard, our results are very close to Dalton et al. (2020) which is rare in that they collect both risk preference measures as well as mental health outcomes in the field setting. They find that owners of small retail businesses in Vietnam exposed to financial worries are more stressed *and* behave less risk-averse than those assigned to placebo treatment.

5. Supplemental evidence from Japan

To assess external relevance, we also examine whether the same results hold among the

[27] Carvalho et al. (2016) exclusively focus on the individuals in low-income households with annual household income below $40,000 in the US.
[28] To our knowledge, Carvalho et al. (2016) did not report the results on mental health.
[29] The average age in Carvalho et al. (2016) is 49 and 56 in Study 1 and 2 which is much younger than the average of 69 years in our sample.
[30] For example, the elderly may experience life stressors not only common to everyone, but also stressors that are more common in later life, like a significant ongoing loss in capacities and a decline in functional ability. The social isolation during the COVID-19 pandemic could exacerbate the mental vulnerability of the elderly (Armitage and Nellums 2020).

elderly in Japan. The public pension in Japan is paid on the 15th of every even month.[31] Stephens and Unayama (2011) show that household consumption is responsive to public pension benefit receipt in Japan. We again compare individuals' risk preferences before and after the payday.

It is worth noting that this exercise is more than a simple replication in another country since the US and Japan have very different baseline risk preferences. Falk et al. (2018) collected the individual preferences from 80,000 people in 76 countries and showed that Japan is one of the most risk-averse countries (#6), whereas the US is on the other side of the spectrum (#52).[32]

Our data comes from the Japanese Study of Aging and Retirement (JSTAR) from 2007-2013. JSTAR is modeled after the HRS, and interview surveys are conducted biennially since 2007. Respondents are those aged over 50 and from 10 municipalities.[33]

JSTAR asks the question of risk preference using hypothetical scenarios. The exact wording of the questionnaire is presented in Appendix Table C2. Risk tolerance is measured by the question on the choice of income from two scenarios, which is conceptually similar to the gamble question in HRS. The safe option guarantees a 20% increase in income, whereas the risky option increases the income by either 50% or 5% with a specific probability. Varying the chance of the downside risk on risky options refines the measure of risk preference. To be consistent with HRS, we derive the risk tolerance parameter θ in the same way, assuming the CRRA utility function. Again, the higher value indicates more risk tolerance.[34]

Appendix Table B2 presents the descriptive statistics of the JSTAR sample. Interestingly, JSTAR respondents heavily rely on pension benefits than HRS respondents. The average share of public pension out of total household income in JSTAR (0.643) is very similar to the share of Social Security benefit in the above-median sample in HRS (0.685). Thus, we do not divide the

[31] If the 15th in the month falls on a weekend or holiday, benefits are paid on the first business day before the 15th, as in the case of Social Security payment in the US.
[32] Authors' calculation based on the data here: https://www.briq-institute.org/global-preferences/rankings#2-0-0 (last accessed on 03/10/2020)
[33] These municipalities are Takikawa City in Hokkaido Prefecture, Sendai City in Miyagi Prefecture, Adachi Ward in the Tokyo metropolis, Kanazawa City in Ishikawa Prefecture, Shirakawa Town in Gifu Prefecture, Naha City in Okinawa Prefecture, Tosu City in Saga Prefecture, Chofu City in the Tokyo metropolis, Tondabayashi City in Osaka Prefecture, and Hiroshima City in Hiroshima Prefecture.
[34] Appendix Table B1 provides the relationship between the eight income response categories and the downside risks. The larger category numbers indicate that individuals are willing to accept higher income risk, and thus the corresponding risk tolerance parameter is larger. Appendix Figure B1 presents the frequency distributions of risk categories, revealing substantial heterogeneity in risk attitudes.

sample by the share of the public pension here to maximize the statistical power (N= 2,728). Following the analysis on HRS, we restrict the sample to the households in which at least one person receives the public pension, and do not live with children or their parents to avoid the influence of the other sources of income. The average age is 68.2 years, which is very similar to the HRS sample (69.2 years). 80.3% are married. Roughly half (51.0%) are female.

Since the payment of public pension in Japan is every two months instead of every month, we slightly modify the equation [1] to include more week dummies as follows:

$$Y_i = \sum_{k\neq+1}^{k=-1,-2,-3,-4,+2,+3,+4} \beta_k 1(week = k) + \gamma X_i' + \delta_{FE} + \varepsilon_i, \quad [1]'$$

Again, our reference week is a week right after the payday ($k = +1$), and our main coefficient of interest is β_{-1}, a coefficient for a week before the payday. In addition to the fixed effects included in equation [1], the two-month intervals between paydays allow us to include the week-of-the-month fixed effects, which is impossible in the case of the US because this data include the calendar months when the pubic pension is not paid (odd months).

Appendix Table B3 reports the results from the test on the randomness of the interview dates. Specifically, we run equation [1]' on predetermined variables in the dataset. The table reports the F-tests and corresponding p-values of the null hypothesis that each of the estimates on the eight-week dummies is equal to zero. Except for age, none of the 11 estimates is statistically significant at the 5% level.[35] In our regressions, we control for all these predetermined variables.

We first present our graphical evidence. Appendix Figure B2 plots the measured risk tolerance with 2-day bins around the payday. As the interval between payments is two months, our synthetic month around the 15th of the month ranges from –28 to +27. The figure shows that the risk tolerance parameter is discontinuously higher just before the payday, indicating that respondents are more risk tolerant before payday in Japan as well.

Table 8 reports the results from estimating equation [1]' without any individual controls in column (1) and with controls in column (2). Column (1) shows that before payday week ($k = -1$) is associated with the increase of risk tolerance by 0.058 ($p<0.05$). This represents a 37.9% increase in risk tolerance from the mean (0.153). None of the other week dummies are statistically significant, suggesting that temporal shift in risk preference is concentrated within one week from the payday. Adding individual controls in column (2) barely changes the estimate

[35] For privacy reasons, geographical information is not available in JSTAR.

on a before-payday week dummy, reassuring that randomization of interview dates are successful. Whereas the country and the sample period are different in HRS and JSTAR, we find similar patterns in both data, which strengthens our external validity of the results.[36]

6. Conclusion

We evaluate the impact of the income fluctuations on measured risk preference among the elderly by exploiting the periodic payday cycles of Social Security payment in the US and public pension payment in Japan. In both countries, we find evidence of temporary but systematic variation in risk preference around payday, suggesting that the risk preference is not temporarily stable in the short intervals at least among the samples of older adults in the 1990s in the US, and in the 2000s in Japan. In particular, individuals become more risk tolerant just before payday when they are most financially strained. The temporal shift in risk preference around payday indicates that optimal decisions made before the payday may turn into non-optimal decisions after the payday. It is important to stress that the results on the risk preference have been found in countries with very different baseline risk preferences (the US and Japan). This suggests that evidence from this study may apply more generally to a broad set of countries with different levels of underlying risk preference.

Furthermore, based on US analysis, our results do not support the hypothesis that financial hardship impedes cognitive function and worsens the quality of decision-making. Instead, we find suggestive evidence that mental state plays some role whereas this is by far not the only reason. The poor elderly who heavily rely on Social Security income for hand-to-mouth life are more depressed before payday than after payday.

This study provides several avenues for future research. First, whereas our across-individual design still allows us to investigate the temporal stability of aggregate risk preference, it is important from the policy perspective to identify the characteristics of individuals who exhibit unstable risk preference, using a within-subjects design. Second, in light of the burgeoning literature on the psychology of the poor (e.g., Schilbach et al. 2016; Kremer et al. 2019), more research is needed to understand the underlying mechanisms for such temporal shifts in preference (e.g., cognition, emotion, and stress). Finally, examining whether our results

[36] Whereas JSTAR also includes depression measure, it was collected by a self-completion questionnaire instead of the face-to-face interview, and as a result, the exact dates of data entry are unknown.

hold in a different subject pool (e.g., non-elderly), and different magnitudes of temporal financial fluctuations with various levels of uncertainty, is an interesting extension. Since periodic payment of welfare programs, pensions and salaries are prevalent in many countries, there is an ample opportunity to apply a similar research design, and investigate whether a similar pattern in risk preference or other preferences (e.g., time and social preferences) can be observed in other settings.

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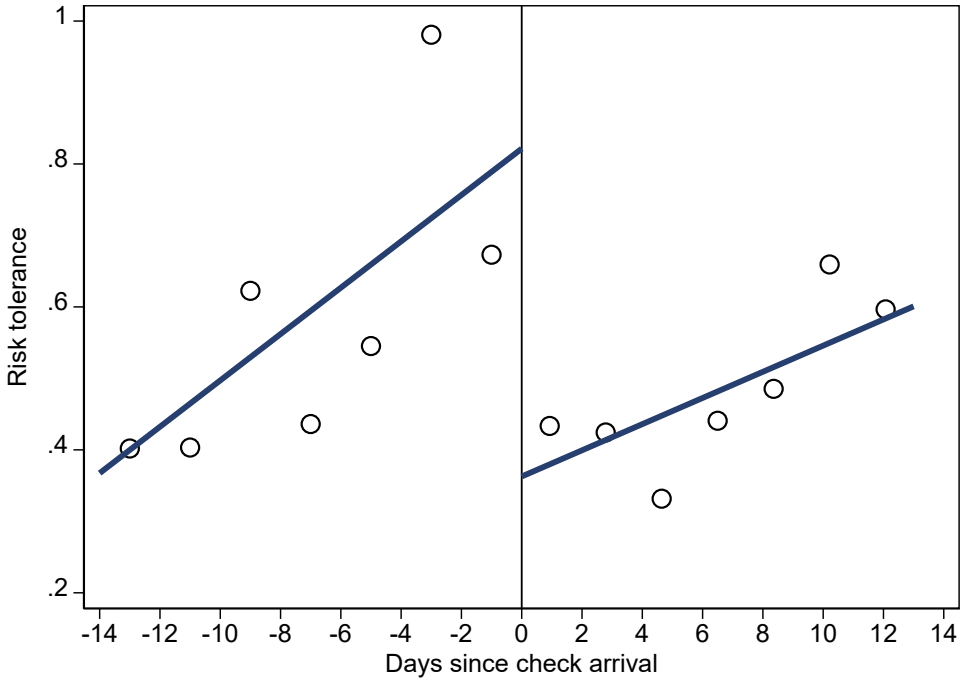
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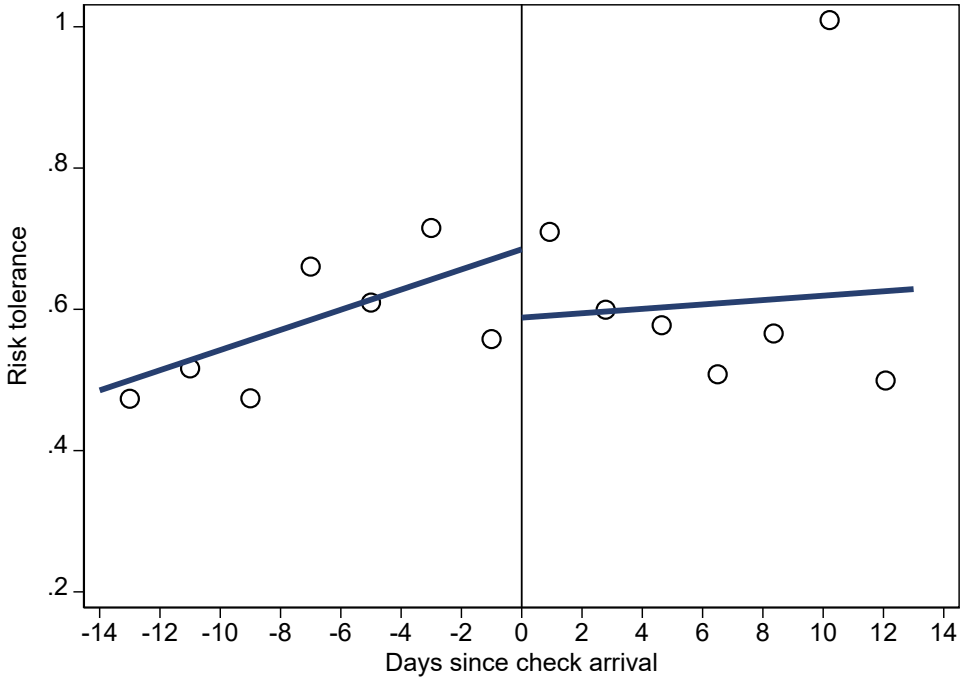
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Figure 1—Risk tolerance before and after payday (HRS)

(a) SS/income share *above* the median
(share>=44%, N=602)



(b) SS/income share *below* the median
(share<44%, N=599)



Notes: Each plot represents the two-day average of risk tolerance for two weeks before and after the check arrival. The line corresponds to the linear fit. The sample is limited to SS/income share *above* the median in panel (a) and *below* the median in panel (b). See the main text for the construction of risk tolerance measures.

Table 1—Descriptive statistics (HRS)

Variables	Obs	Mean	SD	Min	Max
Risk tolerance: θ	1201	0.555	0.848	0.13	3.27
Days since check arrival	1201	0.595	8.57	-14	13
Social security benefits/household income	1201	0.463	0.272	0	1
Nonsavers	1201	0.345	0.475	0	1
Cognition					
Normal	1038	0.832	0.374	0	1
CIND	1038	0.148	0.356	0	1
Demented	1038	0.019	0.138	0	1
Depression	1200	0.122	0.327	0	1
Individual characteristics:					
Age (in years)	1201	69.216	3.349	62	85
Female	1201	0.484	0.500	0	1
Years of schooling	1201	12.359	2.910	0	17
Married	1201	0.911	0.285	0	1
Retired	1201	0.772	0.420	0	1
Household size	1201	1.953	0.211	1	2
Northeast	1201	0.172	0.377	0	1
Midwest	1201	0.295	0.456	0	1
South	1201	0.357	0.479	0	1
West	1201	0.177	0.381	0	1
Good health	1201	0.430	0.495	0	1
Poor health	1201	0.081	0.273	0	1
African American	1201	0.067	0.249	0	1

Notes: The data come from the HRS in 1994, 1998, 2000, 2002, and 2006. Nonsavers are defined as individuals who hold the net value of all savings worth less than $10,000. The measures of cognition are classified as normal, cognitively impaired but not demented (CIND), and demented, which are mutually exclusive. See section 4.3 for the definition of each cognition variable. Depression is a dummy that takes the value of one if the person felt depressed much of the time during the past week.

Table 2—Test for randomization of interview dates

	Age	Female	Yrs. of schooling	Married	Retired	Household size	Northeast	Midwest	South	West	Good health	Poor health	African American
(a) Full sample													
F-stat	1.106	0.825	1.128	1.312	0.600	1.254	3.367	0.209	3.174	5.126	1.255	0.484	1.970
p-value	0.346	0.480	0.336	0.269	0.615	0.289	0.018	0.890	0.023	0.002	0.289	0.694	0.117
N	1201	1201	1201	1201	1201	1201	1201	1201	1201	1201	1201	1201	1201
(b) SS/income share *above* the median													
F-stat	0.377	0.066	0.668	2.047	0.078	1.401	2.627	1.274	4.169	3.580	0.670	1.843	0.792
p-value	0.769	0.978	0.572	0.106	0.972	0.242	0.050	0.282	0.006	0.014	0.571	0.138	0.499
N	602	602	602	602	602	602	602	602	602	602	602	602	602
(c) SS/income share *below* the median													
F-stat	1.289	1.581	2.008	0.079	1.409	0.559	3.575	1.218	0.379	3.544	3.426	0.344	2.190
p-value	0.277	0.193	0.112	0.971	0.239	0.642	0.014	0.302	0.768	0.014	0.017	0.793	0.088
N	599	599	599	599	599	599	599	599	599	599	599	599	599

Notes: F-stats and p-values correspond to tests of the joint null that coefficients on the four-week dummies are each zero.

Table 3—Main results: Risk tolerance

	SS/income share	
	above the median	*below* the median
	(1)	(2)
Week -2	0.021	-0.068
	(0.089)	(0.105)
Week -1	0.287**	0.041
	(0.136)	(0.114)
Week +2	0.151	0.103
	(0.092)	(0.096)
Covariates	×	×
Mean of outcome	0.516	0.594
N	602	599
R squared	0.112	0.207

Notes: The outcome is risk tolerance. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. See the main text for the construction of each preference measure. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 4—Robustness checks: Risk tolerance

	SS/income share			
	above the median	*above* 40 percent	*above* 50 percent	*above* 60 percent
	(1)	(2)	(3)	(4)
Week -2	0.021	0.011	0.066	0.009
	(0.089)	(0.082)	(0.103)	(0.135)
Week -1	0.287**	0.269**	0.362**	0.302*
	(0.136)	(0.122)	(0.147)	(0.180)
Week +2	0.151	0.154*	0.201*	0.057
	(0.092)	(0.087)	(0.105)	(0.119)
Covariates	×	×	×	×
Mean of outcome	0.516	0.515	0.530	0.512
N	602	659	493	346
R squared	0.112	0.124	0.127	0.161
Sample share	*50 percent*	*55 percent*	*41 percent*	*29 percent*

Notes: The outcome is risk tolerance. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 5—Heterogeneity: Risk tolerance

	Nonsavers	Savers
	(1)	(2)
Week -2	0.016	-0.052
	(0.133)	(0.140)
Week -1	0.403**	0.124
	(0.191)	(0.220)
Week +2	0.220	0.029
	(0.144)	(0.151)
Covariates	×	×
Mean of outcome	0.494	0.537
N	290	312
R squared	0.209	0.180

Notes: The sample is limited to SS/income share *above* the median. The outcome is risk tolerance. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Savers is defined as an individual who holds the net value of stocks, mutual funds, and investment trusts, the value of checking, savings, or money market accounts, the value of CD, government savings bonds, and T-bills, the net value of all other savings worth at least $10000. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 6—Cognition

Outcome:	Normal	CIND	Demented
	(1)	(2)	(3)
Week -2	0.045	-0.064	0.019
	(0.049)	(0.048)	(0.019)
Week -1	0.093	-0.067	-0.025
	(0.063)	(0.062)	(0.021)
Week +2	0.060	-0.039	-0.021
	(0.047)	(0.047)	(0.021)
Covariates	×	×	×
Mean of outcome	0.783	0.183	0.032
N	546	546	546
R squared	0.251	0.175	0.357

Notes: The sample is limited to SS/income share *above* the median. The classification is based on a 27-point score composed of the word recall, serial 7, and backward counting tests. Scores between 12 and 27 are classified as normal, between 7 and 11 as cognitively impaired but not demented (CIND), and between 0 and 6 as demented. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 7—Depression

(a) SS/income share *above* the median

Outcome:	Depression		
	OLS	Probit	Logit
	(1)	(2)	(3)
Week -2	-0.047	-0.067	-0.062
	(0.049)	(0.044)	(0.050)
Week -1	0.066*	0.066*	0.077**
	(0.040)	(0.035)	(0.038)
Week +2	-0.035	-0.058	-0.054
	(0.035)	(0.038)	(0.042)
Covariates	×	×	×
Mean of outcome	0.141	0.148	0.148
N	602	555	555

(b) SS/income share *below* the median

Outcome:	Depression		
	OLS	Probit	Logit
	(1)	(2)	(3)
Week -2	0.019	0.026	0.018
	(0.041)	(0.035)	(0.041)
Week -1	0.047	0.042	0.050
	(0.033)	(0.031)	(0.033)
Week +2	-0.034	-0.022	-0.016
	(0.033)	(0.033)	(0.039)
Covariates	×	×	×
Mean of outcome	0.102	0.110	0.110
N	598	541	541

Notes: The sample is limited to SS/income share *above* the median in panel (a) and *below* the median in panel (b). The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The outcome is a dummy that takes the value of one if the person felt depressed much of the time during the past week. The omitted category is week +1. Note that since the reference period of this question is a week from the survey date, we define the week dummies in equation [1] accordingly. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 8—Supplemental analysis from JSTAR: Risk Tolerance

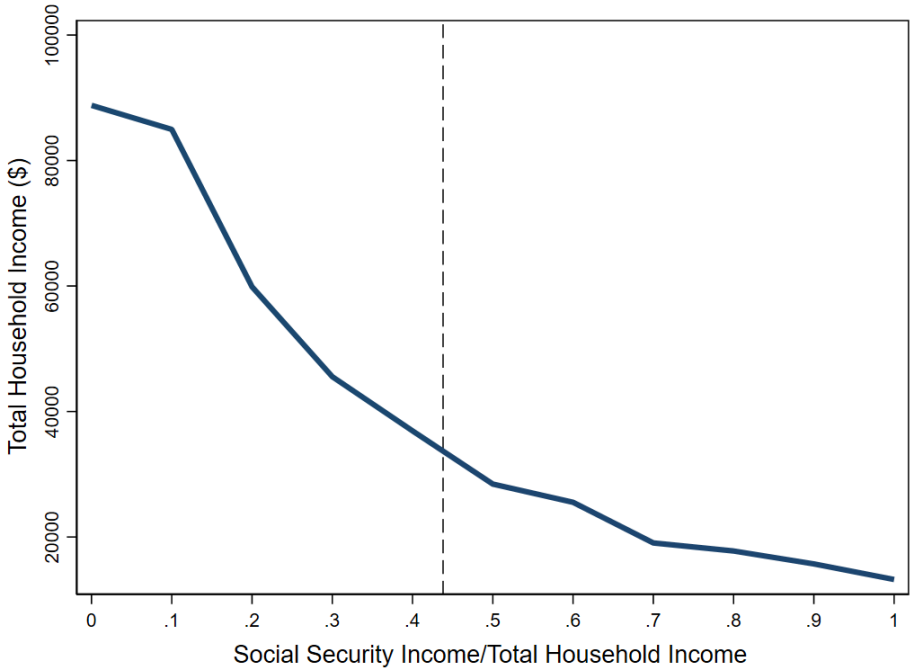
	(1)	(2)
Week -4	-0.017	-0.020
	(0.032)	(0.032)
Week -3	-0.028	-0.026
	(0.039)	(0.038)
Week -2	0.027	0.030
	(0.030)	(0.030)
Week -1	0.056**	0.058**
	(0.027)	(0.027)
Week +2	0.013	0.009
	(0.024)	(0.024)
Week +3	-0.005	-0.004
	(0.029)	(0.029)
Week +4	0.022	0.025
	(0.034)	(0.034)
Covariates		×
Mean of outcome	0.153	0.153
N	2,728	2,728
R squared	0.036	0.055

Notes: The outcome is risk tolerance. The estimates β_k ($k = -4, -3, -2, -1, +2, +3, +4$) from estimating equation [1]' are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, age squared, and dummy variables for gender, married, educational background, sampling cohort, working status, good and bad health status. Time effects are related to the date of the survey-interview and include dummy variables for the year, month, interactions of year and month, day of the week, number of weeks, and interactions of the day of week and number of week of the interview date. See the main text for the construction of risk preference measures. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Online Appendix
(Not for Publication)

Appendix A: Analysis for US (HRS)

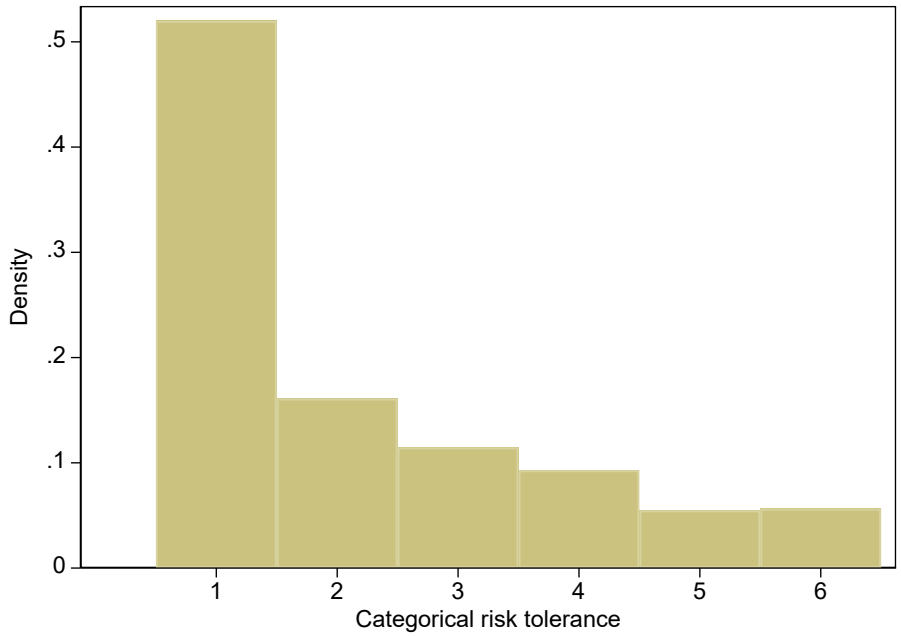
Figure A1—The relationship between the share of Social Security income out of total household income and total household income



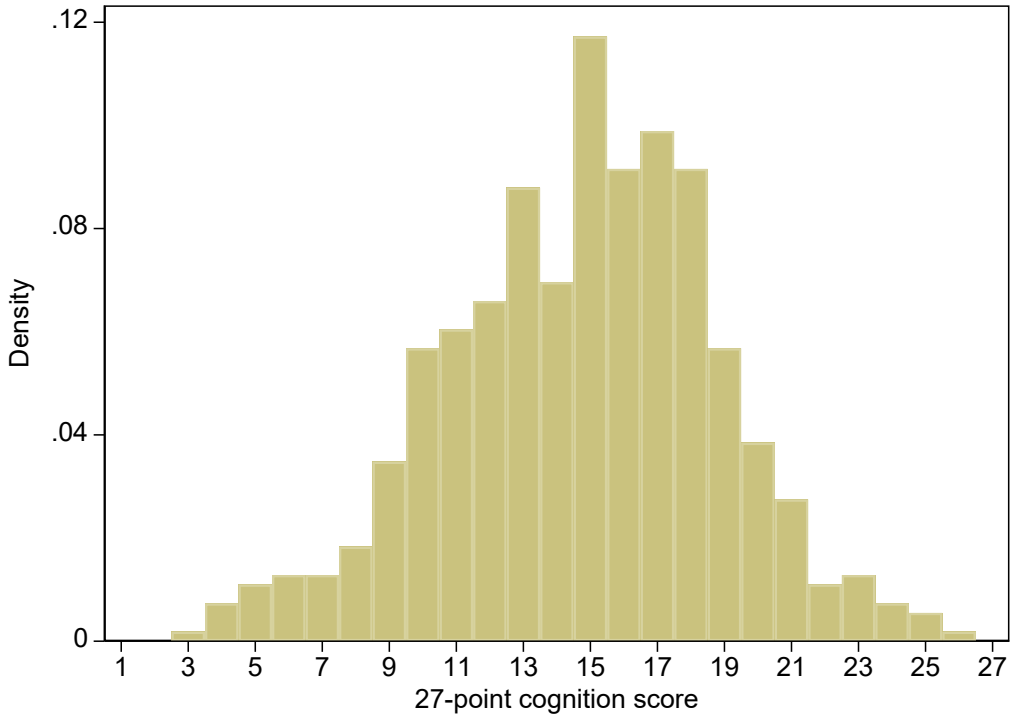
Notes: The data come from the HRS in 1994, 1998, 2000, 2002, and 2006. The x-axis is the share of Social Security income out of total household income, and the y-axis is the total household income. The dotted line is the sample median of the share of Social Security income out of total household income, which corresponds to an income share of at least 44% or 0.44.

Figure A2—Frequency distributions

(a) Risk preferences (N=602)



(b) Cognition (N=546)



Notes: The data come from the HRS in 1994, 1998, 2000, 2002, and 2006. Appendix Table A1 provides the relationship between the gamble response category and the downside risks that the individual accepts and rejects. See Appendix Table C1 for the questionnaires for risk preferences. Cognition is a 27-point score composed of the word recall, serial 7, and backward counting tests.

Table A1—Categories of risk tolerance responses

Response category	Downside risk of risky jobs		Bounds on Risk tolerance: θ		Fraction (%)
	Accept	Reject	Lower	Upper	
1	None	1/10	0	0.13	51.99
2	1/10	1/5	0.13	0.27	16.11
3	1/5	1/3	0.27	0.50	11.46
4	1/3	1/2	0.50	1.00	9.30
5	1/2	3/4	1.00	3.27	5.48
6	3/4	None	3.27	∞	5.65

Notes: The data come from the HRS in 1994, 1998, 2000, 2002, and 2006. Respondents choose between a safe job and a risky job in hypothetical scenarios. With equal chances, a risky job will double the income or cut monthly income by a specific fraction (or downside risk). Varying the downside risk on the monthly income in subsequent questions refines the measure of risk preferences. Panel (a) of Appendix Figure A1 shows the frequency distributions of risk choices. At the lower bound of the risk tolerance category (#1), an individual rejects a risky job with the smallest downside risk. At the upper bound of the risk tolerance category (#6), an individual accepts the largest downside risk. The exact wording of the questionnaire is presented in Appendix Table C1.

Table A2—Robustness checks: Risk tolerance (*below* thresholds)

	SS/income share			
	below median	*below* 40 percent	*below* 50 percent	*below* 60 percent
	(1)	(2)	(3)	(4)
Week -2	-0.068	-0.095	-0.034	-0.005
	(0.105)	(0.117)	(0.093)	(0.081)
Week -1	0.041	0.000	0.043	0.136
	(0.114)	(0.126)	(0.107)	(0.099)
Week +2	0.103	0.075	0.087	0.115
	(0.096)	(0.104)	(0.088)	(0.078)
Covariates	×	×	×	×
Mean of outcome	0.594	0.602	0.572	0.572
N	599	542	708	855
R squared	0.207	0.205	0.170	0.131
Sample share	*50 percent*	*45 percent*	*59 percent*	*71 percent*

Notes: The outcome is risk tolerance. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A3—Other robustness checks: Ordinal outcome of risk preference

	Risk tolerance categories 5 or 6	Ordered Probit
	(1)	(2)
Week -2	-0.025	0.078
	(0.034)	(0.136)
Week -1	0.099*	0.302*
	(0.052)	(0.178)
Week +2	0.034	0.189
	(0.036)	(0.130)
Covariates	×	×
Mean of outcome	0.111	2.171
N	602	602

Notes: The sample is limited to SS/income share *above* the median. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Column (1) replaces the outcome by a binary measure of risk preferences that takes the value of 1 if the person chose the highest or second-highest risk tolerance categories (categories 5 or 6) and 0 otherwise. Column (2) replaces the outcome by an ordinal measure of risk preferences coded from 1 for the lowest risk tolerance category to 6 for the highest category. Covariates include age, age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A4—Regression discontinuity analysis: Risk tolerance

	(1)	(2)
Days before the pension payment	0.998***	1.432***
	(0.257)	(0.387)
Bandwidth (days)	3.603	2.616
Covariates	×	×
N	602	602

Notes: The sample is limited to SS/income share *above* the median. The outcome is risk tolerance. Robust estimates are reported with robust standard errors in parentheses. One common mean square error optimal bandwidth selector for the RD treatment effect estimator is used in column (1), and one common coverage error rate optimal bandwidth selector for the RD treatment effect estimator is used in column (2). The regression is conducted using the "rdrobust" command in Stata software, which is developed by Calonico et al. (2014). Covariates include age, gender, household size, self-reported health indicators, years of schooling, marital status, race, retirement status, and MSA status dummies, and calendar week FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A5—Heterogeneity (Robustness): Risk tolerance

	SS/income share *above* 40 percent		SS/income share *above* 50 percent		SS/income share *above* 60 percent	
	Nonsavers	Savers	Nonsavers	Savers	Nonsavers	Savers
	(1)	(2)	(3)	(4)	(5)	(6)
Week -2	-0.016	-0.013	-0.024	0.038	0.036	-0.000
	(0.121)	(0.128)	(0.151)	(0.148)	(0.182)	(0.209)
Week -1	0.319*	0.179	0.451**	0.271	0.627**	0.239
	(0.169)	(0.203)	(0.206)	(0.245)	(0.247)	(0.287)
Week +2	0.206	0.050	0.209	0.060	-0.024	0.054
	(0.140)	(0.139)	(0.140)	(0.177)	(0.166)	(0.226)
Covariates	×	×	×	×	×	×
Mean of outcome	0.488	0.542	0.492	0.566	0.453	0.570
N	324	335	243	250	172	174
R squared	0.203	0.192	0.278	0.261	0.427	0.303

Notes: The outcome is risk tolerance. The estimates β_k $(k = -2, -1, +2)$ from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Savers is defined as an individual who holds the net value of stocks, mutual funds, and investment trusts, the value of checking, savings, or money market accounts, the value of CD, government savings bonds, and T-bills, the net value of all other savings worth at least $10000. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A6—Placebo: Risk tolerance

	People aged 50 to 61 years	People aged 62+ who do not receive SS
	(1)	(2)
Week -2	-0.039	-0.013
	(0.040)	(0.139)
Week -1	0.011	-0.063
	(0.044)	(0.130)
Week +2	0.045	-0.162
	(0.044)	(0.120)
Covariates	×	×
Mean of outcome	0.533	0.479
N	3,006	340
R squared	0.057	0.221

Notes: The outcome is risk tolerance. The estimates β_k $(k = -2, -1, +2)$ from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Column (1) limits the sample to people aged 50-61 years who are younger than the eligibility age of 62 for Social Security. Column (2) limits the sample to people aged 62 and over who do not yet receive Social Security benefits. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A7—Cognition (Robustness)

	SS/income share *above* 40 percent			SS/income share *above* 50 percent			SS/income share *above* 60 percent		
	Normal	CIND	Demented	Normal	CIND	Demented	Normal	CIND	Demented
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Week -2	0.062	-0.083*	0.021	0.035	-0.051	0.016	-0.003	-0.010	0.013
	(0.047)	(0.046)	(0.018)	(0.055)	(0.055)	(0.022)	(0.070)	(0.069)	(0.028)
Week -1	0.065	-0.052	-0.013	0.086	-0.071	-0.015	0.129	-0.112	-0.017
	(0.060)	(0.060)	(0.019)	(0.068)	(0.067)	(0.023)	(0.093)	(0.090)	(0.033)
Week +2	0.055	-0.043	-0.012	0.061	-0.051	-0.010	0.061	-0.056	-0.005
	(0.045)	(0.045)	(0.019)	(0.055)	(0.055)	(0.024)	(0.068)	(0.068)	(0.033)
Covariates	×	×	×	×	×	×	×	×	×
Mean of outcome	0.786	0.183	0.030	0.774	0.193	0.031	0.732	0.226	0.041
N	600	600	600	444	444	444	314	314	314
R-squared	0.237	0.166	0.330	0.272	0.195	0.380	0.310	0.239	0.442

Notes: The classification is based on a 27-point score composed of the word recall, serial 7, and backward counting tests. Scores between 12 and 27 are classified as normal, between 7 and 11 as cognitively impaired but not demented (CIND), and between 0 and 6 as demented. The estimates β_k ($k = -2, -1, +2$) from estimating an equation [1] are reported with robust errors in parentheses. The omitted category is week +1. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table A8—Depression (Robustness)

(a) SS/income share *above* thresholds

	SS/income share *above* 40 percent			SS/income share *above* 50 percent			SS/income share *above* 60 percent		
	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Week -2	-0.015	-0.029	-0.030	-0.041	-0.062	-0.062	-0.017	-0.077	-0.072
	(0.047)	(0.044)	(0.050)	(0.053)	(0.048)	(0.056)	(0.068)	(0.057)	(0.064)
Week -1	0.072*	0.066*	0.076**	0.086*	0.068*	0.076*	0.112*	0.120**	0.126**
	(0.039)	(0.035)	(0.037)	(0.048)	(0.041)	(0.046)	(0.061)	(0.048)	(0.052)
Week +2	-0.043	-0.071	-0.065	-0.009	-0.032	-0.032	-0.000	-0.022	-0.017
	(0.033)	(0.037)	(0.041)	(0.043)	(0.043)	(0.050)	(0.057)	(0.058)	(0.067)
Covariates	×	×	×	×	×	×	×	×	×
Mean of outcome	0.144	0.154	0.154	0.144	0.160	0.160	0.173	0.178	0.178
N	659	610	610	493	450	450	346	313	313
R-squared	0.175	-	-	0.234	-	-	0.329	-	-

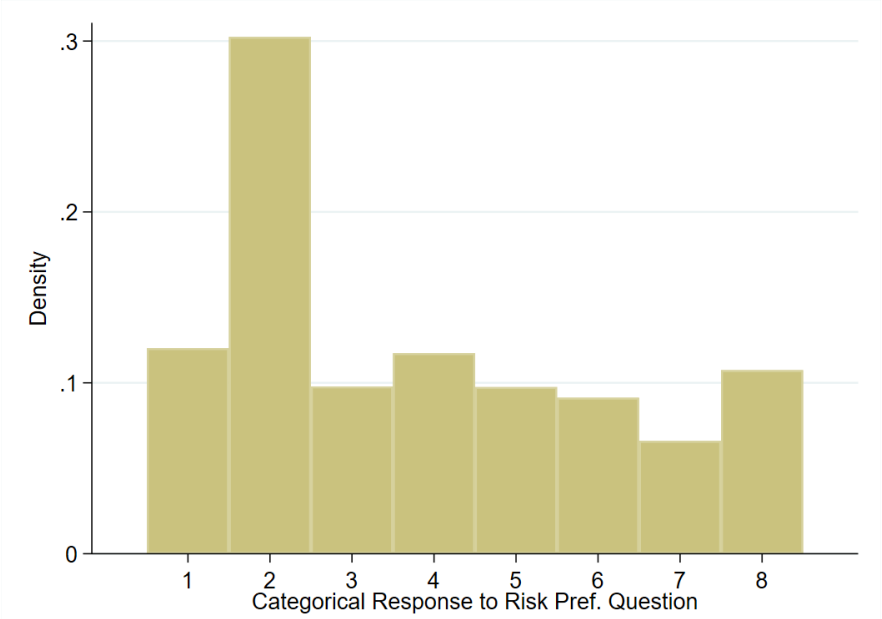
(b) SS/income share *below* thresholds

	SS/income share *below* 40 percent			SS/income share *below* 50 percent			SS/income share *below* 60 percent		
	OLS	Probit	Logit	OLS	Probit	Logit	OLS	Probit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Week -2	0.023	0.032	0.028	-0.007	-0.005	-0.009	0.004	0.003	0.006
	(0.042)	(0.037)	(0.043)	(0.039)	(0.034)	(0.038)	(0.034)	(0.030)	(0.033)
Week -1	0.031	0.024	0.032	0.008	0.000	0.008	0.029	0.020	0.029
	(0.033)	(0.032)	(0.034)	(0.032)	(0.028)	(0.028)	(0.028)	(0.025)	(0.026)
Week +2	-0.008	0.005	0.014	-0.060**	-0.054*	-0.049	-0.043*	-0.044	-0.041
	(0.036)	(0.034)	(0.040)	(0.029)	(0.031)	(0.035)	(0.026)	(0.031)	(0.032)
Covariates	×	×	×	×	×	×	×	×	×
Mean of outcome	0.094	0.106	0.106	0.100	0.104	0.104	0.100	0.106	0.106
N	541	471	471	707	668	668	854	801	801
R-squared	0.215	-	-	0.180	-	-	0.149	-	-

Notes: The estimates β_k $(k = -2, -1, +2)$ from estimating an equation [1] are reported with robust errors in parentheses. The outcome is a dummy that takes the value of one if the person felt depressed much of the time during the past week. The omitted category is week +1. Note that since the reference period of this question is a week from the survey date, we define the week dummies in equation [1] accordingly. Covariates include age, gender, household size, self-reported health indicators, highest years of schooling, marital status, race, retirement status, and MSA status dummies, calendar week FEs, year FEs, month FEs, and year-month FEs. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

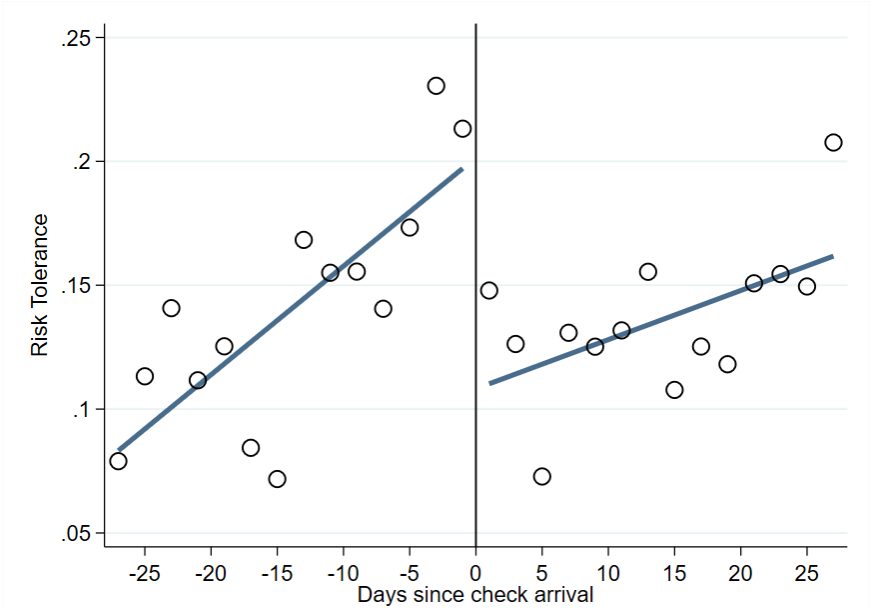
Appendix B: Analysis for Japan (JSTAR)

Figure B1—Frequency distributions



Notes: Appendix Table B1 provides the relationship between the gamble response category and the downside risks that the individual accepts and rejects. The exact wording of the questionnaire is presented in Appendix Table C2 (N= 2,728).

Figure B2—Risk tolerance before and after payday (JSTAR)



Notes: Each plot represents the two-day average of risk tolerance residualized by survey-interview date FEs (N = 2,728) for four weeks before and after the check arrival. The survey-interview date FEs include dummy variables for the year, month, interactions of year and month, day of the week, number of weeks, and interactions of the day of week and number of the week. The line corresponds to the linear fit. See the main text for the construction of risk tolerance measures. Note that public pension benefit in Japan is paid on the 15th of every *two* months.

Table B1—Categories of risk tolerance responses (JSTAR)

Response category	Pay choices		Bounds on Risk tolerance: θ		Fraction
	Choice 1	Choice 2	Lower	Upper	(%)
1	100% chance of an increase by 50%	100% chance of an increase by 20%	-	0.00	12.02
2	90% chance of an increase by 50% and 10% chance of an increase by 5%		0.00	0.06	30.24
3	80% chance of an increase by 50% and 20% chance of an increase by 5%		0.06	0.08	9.79
4	70% chance of an increase by 50% and 30% chance of an increase by 5%		0.08	0.11	11.73
5	60% chance of an increase by 50% and 40% chance of an increase by 5%		0.11	0.16	9.75
6	50% chance of an increase by 50% and 50% chance of an increase by 5%		0.16	0.25	9.13
7	40% chance of an increase by 50% and 60% chance of an increase by 5%		0.25	0.62	6.60
8	-		0.62	∞	10.74

Notes: Data come from the Japanese Study of Aging and Retirement (JSTAR) in 2007, 2009, 2011, and 2013. Respondents choose income from two scenarios where the safe option guarantees a 20% increase in income, while the risky option increases the income by either 50% or 5% with a specific probability. Varying the downside risk on risky options refines the measure of risk preferences. At the upper bound of the risk tolerance category (#8), an individual accepts the largest downside risk. Appendix Figure B1 shows the frequency distributions of risk choices. The exact wording of the questionnaire is presented in Appendix Table C2.

Table B2—Descriptive statistics (JSTAR)

Variables	Obs	Mean	SD	Min	Max
Risk tolerance: θ	2,728	0.153	0.195	0	0.62
Days since check arrival	2,728	-0.932	15.094	-28	27
Social Security Benefits / Household Income	2,388	0.642	0.313	0	1
Individual Characteristics:					
Age	2,728	68.515	4.992	51	81
Female	2,728	0.510	0.500	0	1
Education					
Elementary/Middle school	2,728	0.312	0.464	0	1
High School	2,728	0.462	0.499	0	1
Junior College	2,728	0.040	0.195	0	1
Vocational School	2,728	0.059	0.236	0	1
University or above	2,728	0.127	0.333	0	1
Married	2,728	0.803	0.398	0	1
Not working	2,728	0.615	0.487	0	1
Good Health	2,728	0.342	0.475	0	1
Poor Health	2,728	0.138	0.345	0	1

Notes: The data come from the JSTAR in 2007, 2009, 2011, and 2013.

Table B3—Test for randomization of interview dates (JSTAR)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
			Education								
	Age	Female	Elementary/ Middle school	High School	Junior College	Vocational School	University or above	Married	Not Working	Good Health	Poor Health
F-stat	2.482	0.629	0.970	1.674	1.643	1.274	0.584	0.770	1.067	1.474	0.746
p-value	0.016	0.732	0.452	0.112	0.120	0.261	0.770	0.613	0.383	0.173	0.633

Notes: F-stats and p-values correspond to tests of the joint null that coefficients on the eight-week dummies are each zero.

Appendix C: Data Appendix

Table C1—Questionnaire for HRS

Question 0:
Suppose that you are the only income earner in the family. Your doctor recommends that you move because of allergies, and you have to choose between two possible jobs.
The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50-50 chance the second job would double your total lifetime income and a 50-50 chance that it would cut it by a third. Which job would you take -- the first job or the second job?

1. FIRST JOB → to Question C
2. SECOND JOB → to Question A
8. Don't know / Not available → End
9. Refuse → End

Question A:
Suppose the chances were 50-50 that the second job would double your lifetime income, and 50-50 that it would cut it in half. Would you take the first job or the second job?

1. FIRST JOB → End
2. SECOND JOB → to Question B
8. Don't know / Not available → End
9. Refuse → End

Question B:
Suppose the chances were 50-50 that the second job would double your lifetime income and 50-50 that it would cut it by seventy-five percent. Would you take the first job or the second job?

1. FIRST JOB → End
2. SECOND JOB → End
8. Don't know / Not available → End
9. Refuse → End

Question C:
Suppose the chances were 50-50 that the second job would double your lifetime income and 50-50 that it would cut it by twenty percent. Would you take the first job or the second job?

1. FIRST JOB → to Question D
2. SECOND JOB → End
8. Don't know / Not available → End
9. Refuse → End

Question D:
Suppose the chances were 50-50 that the second job would double your lifetime income and 50-50 that it would cut it by 10 percent. Would you take the first job or the second job?

1. FIRST JOB → End
2. SECOND JOB → End
8. Don't know / Not available → End
9. Refuse → End

Table C2—Questionnaire for JSTAR

Question: Suppose how you are paid at work were to change next month only, which of the following options would you prefer? Please assume that the amount of your pay is not related to your ability or effort and that this change will be in effect for the next month only.

Choice 1	Choice 2
100% chance of an increase by 50%	100% chance of an increase by 20%
90% chance of an increase by 50% and 10% chance of an increase by 5%	
80% chance of an increase by 50% and 20% chance of an increase by 5%	
70% chance of an increase by 50% and 30% chance of an increase by 5%	
60% chance of an increase by 50% and 40% chance of an increase by 5%	
50% chance of an increase by 50% and 50% chance of an increase by 5%	
40% chance of an increase by 50% and 60% chance of an increase by 5%	