# Framing Social Security Reform:

# Behavioral Responses to Changes in the Full Retirement Age

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Web Appendix

## Data appendix

The main features of the data are described in section IV. This appendix describes in more detail the variables used to differentiate cognitive and behavioral types. Most variables are derived from the raw HRS files.

**Cognitive variables:**

*High TICS score.* The TICS variable provides an objective measure of the respondent's memory and ability to think quickly. This is the sum of points (1 for each correct answer) for a set of questions the respondent has answered; it ranges from 0 to 10. The variable was only collected in waves 3-8 of the HRS. We average the scores for all available waves. We use a dummy for high average TICS scores (above 9).

*High episodic memory*. As part of the interview the interviewer asks the respondent to listen to and then recall a list of words. This variable indicates how many words the respondent can recall immediately after hearing them. In waves 1 and 2, the list included 20 words. In subsequent waves, the list included 10 words. The score for waves 1 and 2 was divided by 2 for comparability. A second variable indicates how many words the respondent can recall some time after hearing the list, i.e, after answering a few other questions. We average the two scores, and then average the resulting measure over all available waves. We then use a dummy for high average memory:  a score higher than 5 out of 10.

*High numeracy.* The numeracy variable is the number of correct answers to the following three questions: Correctly answer the question "If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?"; "If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?"; "Let's say you have $200 in a savings account. The account earns 10 percent interest per year. How much would you have in the account at the end of two years?" These questions were only asked during waves 6 to 8 of the HRS. We average the scores for all available waves. We generate an indicator variable for high numeracy, indicating at least two correct answers out of three on average.

We construct a cognitive index equal to a weighted sum of the TICS, memory and numeracy scores (putting a weight 3.3 times as large on numeracy, to compensate for the smaller range of values). The index can go from 0 to 30.

**Behavioral variables**

*High self control*. We create a self-control score using a series of 5 questions such as "I feel that I can do as I please. (Often? Sometimes? Not often? Never?)." The maximum score is 19, and we generate an indicator for high self control that equals 1 for people with a score higher than 6.

The next two variables come from the RAND release of the HRS:

*Long financial planning horizon.* The "long financial planning horizon" dummy is equal to 1 for those who respond to plan at least for the next few years.

*Risk averse.* The "risk averse" dummy is equal to 1 for workers classified as the most risk averse (out of four categories). This is based on a set of income gamble questions. In these questions the respondent is asked to choose between pairs of jobs where one guarantees current family income and the other offers a chance to increase income but also carries the risk of loss of income. If the respondent says he/she would take the risk, the same scenario but with riskier odds is presented. If the respondent says he/she would not take the risk, the same scenario with less risky odds is asked.

**Working condition variables**

These are from the following questions: “I'll read some statements that are true for some people's jobs but not for other people's jobs. Thinking of your job, please tell how often these statements are true.”

- My job requires lifting heavy loads.
- My job requires lots of physical effort.
- My job requires stooping, kneeling, or crouching.
- My job requires good eyesight.
- My job involves a lot of stress.

*Stressful job* is an indicator variable for responding “all or almost all of the time” or “most of the time” to the last item.

*Physically demanding job* is an indicator variable for being in the top half of the sample for a synthetic variable summing answers to the first three items.

## LEHD Appendix

In this Appendix, we describe evidence from the LEHD on how the change in the FRA has affected the timing of labor force exit. The LEHD Infrastructure File system is based on state Unemployment Insurance (UI) administrative files, with data available from 31 states covering about 80% of the U.S. work force for the years 1990-2004, although the period covered varies by state (Abowd, Haltiwanger, and Lane, 2004). Employers covered by UI file a quarterly report for each individual who received any covered earnings in the quarter. UI covers about 96% of private non-farm wage-salary employment, with lower coverage of agricultural and government workers, and no coverage of the unincorporated self-employed. The UI records contain the individual's Social Security number, and an identification number and quarterly earnings for each employer from which he has any covered earnings during the quarter. These data are merged by the Census Bureau with the Census Personal Characteristics File, which contains the exact date of birth, place of birth, sex, and a measure of race/ethnicity.[1]

The main advantage of the LEHD for our analysis is the very large sample size. The main disadvantages are absence of information on hours of work, and lack of data after the third quarter of 2004. Without data on hours of work, we must use changes in quarterly earnings to infer changes in employment status. The absence of data beyond the third quarter of 2004 means that only two of the "treated" birth cohorts (1938 and 1939) can be used to analyze changes in labor force behavior around age 65.

The main outcome of interest is a binary indicator of zero earnings in a given quarter, conditional on positive earnings in the previous quarter, which we interpret as the hazard of labor force exit. We aggregate the data into cells defined by month and year of birth (January 1931 through December 1942), calendar quarter (1994:Q1 through 2004:Q3, although not all quarters are represented for all cohorts), and age in quarters (62.0, 62.25, 62.5,..., 66.0), and conduct the analysis using cell means, with no loss of information. Data are available for 2,400 cells, with

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[1]An extensive discussion of the construction and the content of these files is provided in Abowd *et al.* (2009). We use a subsample of the full LEHD files, consisting of workers who were employed at any employer at which a member of the 1990-2001 panels of the Survey of Income and Program Participation (SIPP) worked. This is a very large subsample of the full LEHD, somewhat skewed toward large firms. See Blau and Shvydko (2011) for a description of the subsample. In order to reduce the number of quarterly observations from the hundreds of millions to the more manageable level of several million, we use data from only three states. Census Bureau guidelines prevent us from identifying the three states.

roughly 1,000 individual observations per cell on average. Men and women are pooled and gender and state dummies (fractions, after aggregation) are included in the regression models.

The specification used in column 1 of table A-1 is the same as in tables 1-3 in the text. Age and birth year dummies are included, so that the effect of the FRA variable is identified from the interaction of age and birth cohort.[2] The results are consistent with the estimates using the HRS, with a positive FRA effect on the exit hazard, significantly different from zero. Given the fact that we have only two post-reform cohorts, we check a new specification in column 2. The FRA indicator is interacted with cohort dummies: so, the coefficient on the FRA*(coh=1938) variable can be interpreted as the average impact of the FRA for cohort 1938, compared to individuals of the same age in the 1931-37 cohorts, and accounting for cohort trends. The results are unexpected for the 1938 cohort: reaching the FRA *decreases* the hazard of exit. The effect for cohort 1939 is small and statistically insignificant. The specification in column 2 has the advantage of being less restrictive than in column 1, as it does not force the magnitude of the FRA effects to be the same for all cohorts, but it also uses less information: in column 1, the spike at the FRA observed in the 1931-37 cohorts and its decline afterwards contribute to the identification of the FRA coefficient, whereas the estimate in column 2 only tests for the emergence of spikes at the new FRAs.[3]

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[2] If a worker leaves employment at his FRA, his earnings will be positive in the quarter in which his FRA falls (unless he quits on the first day of the quarter), so zero earnings in the first calendar quarter after the quarter in which he reaches his FRA is the only reliable measure of exit at the FRA. Depending on birth month within a quarter, some cases do not provide any evidence on the impact of the change in the FRA. A more detailed discussion of which cases contribute to identification is available from the authors.

[3] We constructed graphs like those in Figures 2-4 and estimated models with non-parametric specifications (like those in Mastrobuoni, 2009, but for hazards rather than levels). The results were similar to the HRS results in Figure 3, showing clear evidence of a decline in the hazard at 65, but less clear evidence of increases at other ages. We omit these results for brevity, but they are available on request. We also analyzed exit from employment in the HRS data using the same cohorts as in the LEHD data and interacting the FRA indicator with indicators for the 1938 and 1939 cohorts; estimates of the FRA impact go in the same direction: 0.5 (0.5) when pooling all sources of identification like in column 1 of table 4; -0.9 (0.8) and 1.6 (1.2) for the FRA indicator interacted with birth cohorts 1938 and 1939, respectively. This contrasts with the claiming results, where the FRA impact is positive (and significant) in all specifications, as can be expected from figure 2.

## Table A-1: Impact of the FRA on the Hazard of Exit from Employment (LEHD data)

| | Exit from Employment | |
|---|---|---|
| | (1) | (2) |
| FRA*(coh=1938) | | -2.8*** |
| | | (0.7) |
| FRA*(coh=1939) | | -0.1 |
| | | (1.6) |
| FRA | 1.2** | |
| | (0.5) | |
| Cohorts | 1931-42 | 1931-42 |
| Age range | 62-66 | 62-66 |
| N | 2256 | 2256 |
| $R^2$ | 0.97 | 0.97 |

Notes: The dependent variable is a dummy for the first quarter with 0 earnings, interpreted as exit from employment. Data are means over cells defined by the month of birth, observed in a given quarter. Each regression includes a full set of monthly age dummies and birth cohort dummies. Controls: gender and state dummies (fraction, after aggregation). *, **, and *** indicate that the coefficient estimate is significantly different from zero at the 10%, 5%, and 1% level, respectively.
Sample: LEHD from three states.

**Model Appendix**

Here we show the results stated in section VI.

Starting from a situation without loss aversion ($\lambda_1 = \lambda_2 = 1$), an increase in $\lambda_1$ attracts workers who would otherwise work longer toward the FRA, thus reducing the average retirement age: $dP_{FRA-} / d\lambda_1 = 0$, $dP_{FRA} / d\lambda_1 > 0$ and $dP_{FRA+} / d\lambda_1 < 0$. An increase in $\lambda_2$ attracts workers who would otherwise retire earlier toward the FRA, thus increasing the average retirement age: $dP_{FRA-} / d\lambda_2 < 0$, $dP_{FRA} / d\lambda_2 > 0$ and $dP_{FRA+} / d\lambda_2 = 0$.

Impact of the 1983 reform: the probability of retiring before the FRA ($P_{FRA-}$) increases, whereas the probability of retiring after the FRA ($P_{FRA+}$) decreases. This can be directly seen from

$$P_{FRA-} = 1 - F\left( w\lambda_2 \frac{v'(c_{FRA})}{u'(l_{FRA})} \right); \qquad \text{(A.1)}$$

$$P_{FRA+} = F\left( \frac{w}{\lambda_1} \frac{v'(c_{FRA})}{u'(l_{FRA})} \right), \qquad \text{(A.2)}$$

noting that $d\,\dfrac{v'(c_{FRA})}{u'(l_{FRA})} = -\dfrac{v'(c_{FRA}) \times u''(l_{FRA})}{\left(u'(l_{FRA})\right)^2} dl_{FRA} < 0.$

Under framing option 1: $\dfrac{dl^*(a)}{dk} = \dfrac{au''(l) + w^2 v''(W - wl)}{wv''(W - wl)}$ so that

$$\left[\frac{dE(R)}{dk}\right]_1 = -\int \frac{au''(l) + w^2 v''(W - wl)}{wv''(W - wl)} f(a)da \text{ , where } W = k + wT,$$

Under framing options 2 and 3 the optimal retirement age is

$$l^* = \begin{cases} l \quad st \quad a\lambda_1 u'(l) - wv'(W - wl) = 0 & for \quad a < \underline{a} \\ l_{FRA} & for \quad a \in \left[\underline{a}; \overline{a}\right] \\ l \quad st \quad au'(l) - w\lambda_2 v'(W - wl) = 0 & for \quad a < \overline{a} \end{cases}$$

with $\underline{a} \equiv \dfrac{wv'(W - wl_{FRA})}{a\lambda_1 u'(l_{FRA})}$ and $\overline{a} \equiv \dfrac{w\lambda_2 v'(W - wl_{FRA})}{au'(l_{FRA})}$. In the second framing option, due to the reduction in benefits at the FRA, the thresholds for being below, at or above the FRA become $\underline{a}' \equiv \dfrac{wv'(W + dW - wl_{FRA})}{a\lambda_1 u'(l_{FRA})}$ and $\overline{a}' \equiv \dfrac{w\lambda_2 v'(W + dW - wl_{FRA})}{au'(l_{FRA})}$. However, for a marginal change *dk*, the probability that $a \in [\underline{a}';\underline{a}]$ or $a \in [\overline{a}';\overline{a}]$ is 0, so that we can neglect these marginal workers when computing the impact of the reform on the expected retirement age. We are left with three categories of workers. Those with low preference for leisure respond to the benefit cut by $\frac{dl^*(a)}{dk} = \frac{a\lambda_1 u''(l) + w^2 v''(W-wl)}{wv''(W-wl)}$, and those with high preference for leisure respond by $\frac{dl^*(a)}{dk} = \frac{au''(l) + w^2 v''(W-wl)}{w\lambda_2 v''(W-wl)}$. However, workers with intermediate preference for leisure do *not* respond to the benefit cut: setting aside the marginal workers, they are such that $a \in [\underline{a}';\overline{a}']$ and they stay at the FRA. So, the impact of the reform under the second framing option is

$$\left[\frac{dE(R)}{dk}\right]_2 = -\int_{-\infty}^{\underline{a}} \frac{a\lambda_1 u''(l) + w^2 v''(W-wl)}{wv''(W-wl)} f(a)da - \int_{\overline{a}}^{+\infty} \frac{au''(l) + w^2 \lambda_2 v''(W-wl)}{w\lambda_2 v''(W-wl)} f(a)da.$$

In the third framing option, workers with low and high preference for leisure respond as in the second option, but workers with intermediate preferences for leisure also respond. The condition for claiming at the FRA is the same as under the second framing option: $a \in [\underline{a}';\overline{a}']$. However, the FRA itself changes, with $dl_{FRA} = \frac{1}{w}dk$. Consequently, these workers delay claiming by $\frac{1}{w}dk$. The impact of the reform on the mean retirement age in this case is

$$\left[\frac{dE(R)}{dk}\right]_3 = \begin{bmatrix} -\int_{-\infty}^{\underline{a}} \frac{a\lambda_1 u''(l) + w^2 v''(W-wl)}{wv''(W-wl)} f(a)da \\ -\int_{\overline{a}}^{+\infty} \frac{au''(l) + w^2 \lambda_2 v''(W-wl)}{w\lambda_2 v''(W-wl)} f(a)da - \frac{1}{w} P_{FRA} \end{bmatrix}.$$

## Simulation Appendix

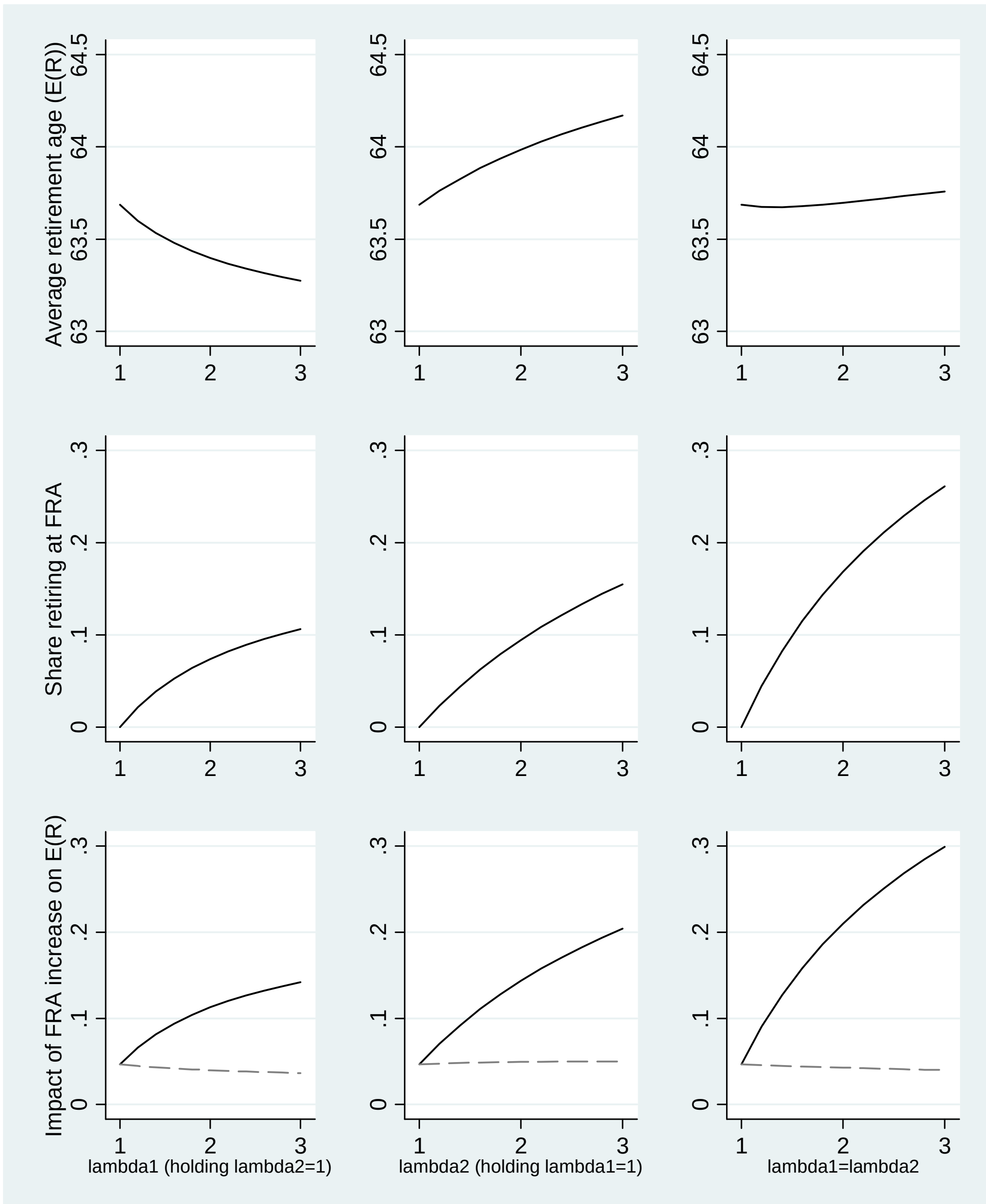
Figure A-1 summarizes the main lesson of the model using simulated data. We use CRRA specifications for *u* and *v* and assume that leisure preference *a* follows a log-normal distribution with mean 1. We set $w$=1 and $k$=0, and simulate the model for various values of the risk aversion coefficients in *u* and *v* and the variance of the log-normal distribution. We select only those simulations that yield plausible distributions of the retirement age.[4] We then take averages across the corresponding simulations.[5] The graphs show the simulated impact of loss aversion (x-axis) on (i) the average retirement age before the reform (top row); (ii) the share of workers retiring exactly at the FRA before the reform (middle row); and (iii) the impact of the reform on the average retirement age (bottom row). The latter impact is analyzed under two framing options: the reform is framed as an increase in the FRA (dark full line, "framing option number 3") or the reform is framed as a cut in the PIA (dashed grey lines, "framing option number 2"). The first framing option (neutral framing) corresponds to the point with $\lambda_1 = \lambda_2 = 1$ on the x-axis. At that point, there is no loss aversion, and framing does not matter (assuming, as discussed above, that there was no framing effect before the reform: even though workers would display loss aversion if there was a reference, when no reference is given everything happens as if people were not loss averse). The three columns correspond to different assumptions on loss aversion: in column 1, workers suffer only from loss aversion with regard to leisure time below their reference; in column 2, workers suffer only from loss aversion with regard to benefits below their reference; in columns 3, the two types of loss aversion are combined.

Looking at the first row illustrates the fact that the impact of loss aversion on the average retirement age is, in general, indeterminate. As noted above, aversion with regard to loss of leisure reduces the average retirement age (top graph on the left), but aversion with regard to loss of benefits increases it (middle graph on the top). The combined effect is, in general, almost 0 (top graph on the right). By contrast, the two types of loss aversion both cause an increase in the size of the spike at the FRA (middle row). Finally, the bottom row shows the crucial role played by framing in the presence of loss aversion. In the absence of framing effects (which corresponds to $\lambda_1 = \lambda_2 = 1$), the reform – modeled here as a 1-year increase in the FRA or a 6.7% benefit cut (as in the 1983 reform) – increases the average retirement age by less than one month (this is represented by the point $\lambda_1 = \lambda_2 = 1$ on the horizontal axis in the bottom three graphs). In the presence of strong loss aversion, framing the reform as an increase in the FRA strongly magnifies the impact, to about 4 months if $\lambda_1 = \lambda_2 = 3$ (bottom right graph, solid line). By

[4] Specifically, we drop simulations with sets of parameters that lead to less than 72% of workers retiring before the FRA, and more than 20% retiring after the FRA, in the absence of loss aversion ( $\lambda_1 = \lambda_2 = 1$).

contrast, the impact of the reform is about the same as in the no-loss-aversion case if the reform is framed as a cut in the PIA (bottom right graph, dashed line). The loss aversion parameters $\lambda_1$ and $\lambda_2$ have strong implications for the impact of the SS reform on retirement age. Even though they are hard to estimate, the simulations suggest that the amplifying effect is roughly proportional to the share of workers clustered at the FRA. This motivated our empirical attempt above at quantifying the magnitude of the spike at the FRA.

## Figure A-1: Simulated Effects of Framing with Different Degrees of Loss Aversion




Note: The graphs show the simulated impact of loss aversion (x-axis) on (i) the average retirement age before the 1983 reform (top row); (ii) the share of workers retiring exactly at the FRA before the 1983 reform (middle row); (iii) the impact of 1983 reform on the average retirement age (bottom row). The latter impact is analyzed under two framing options: the reform is framed as an increase in the FRA (dark full line) or the reform is framed as a cut of the PIA (dashed grey lines).

The three columns correspond to different assumptions on loss aversion: in column 1, values above 1 on the x-axis ($\lambda_1 > 1$) mean that workers suffer only from aversion with regard to cuts in leisure time below their reference; in column 2, values above 1 on the x-axis ($\lambda_2 > 1$) mean that workers suffer only from aversion with regard to cuts in benefits below their reference; in columns 3, the two types of loss aversion are combined. In all graphs, 1 on the x-axis ($\lambda_1 = \lambda_2 = 1$) is the case with no loss aversion. The slope of the curves in each graph shows the impact of increasing loss aversion.

**Appendix References**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