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Communicating Social Security Reform
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ABSTRACT

Despite its centrality in monetary policy, communication is not a focus in social security reform. We investigate the potential for active communication to dissipate apparently widespread public confusion about the future of social security. We implement a simple information treatment in which we randomly provide survey respondents access to the longevity-based eligibility age implemented by reform that Denmark launched in 2006. Absent treatment, younger workers not only have biased beliefs, expecting to become eligible for social security earlier than policy makers intend, but also are highly uncertain about eligibility age. The information treatment eliminates the bias, suggesting it results from misunderstanding. Yet it has no influence on uncertainty, suggesting this is driven by unavoidable demographic and political uncertainties. Our results highlight the value of communication strategies and belief measurement as policy instruments outside the monetary policy arena.

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1 Introduction

Communication is now a critical aspect of monetary policy design.[1] Central banks routinely announce inflation targets and their plans for achieving them in the form of "forward guidance". Household and firm surveys of inflation expectations are conducted to identify the extent to which these announcements achieve their goal of being credible and comprehensible.[2]

Policy communication is not a focus in social security reform. In this paper we show it should be: coordinating policy change with communication and measurement of public perception is crucial.[3] With populations aging and fiscal pressures growing, reforms such as delays in eligibility age are being considered and instituted worldwide (Börsch-Supan and Coile, 2018). Such changes are highly salient to workers: social security is a notoriously powerful determinant of late-in-life labor supply,[4] and hence impacts spending and savings decisions. Knowing this, policy makers announce future changes well in advance to help workers plan better.[5] Denmark is a particularly striking case in point: it set in place plans for major changes in eligibility age back in 2006, far earlier than other countries and more ambitious in scope. This reform replaced a long-standard policy with universal social security eligibility at age 65 with longevity-based eligibility (The Welfare Agreement), and that information was made public. The reform changed **only** eligibility age, without changing other features of the social security benefit system. Given this one dimensional nature, the salience of eligibility age, and the online availability of policy plans, one might expect the public to be aware of planned increases in eligibility age. Yet, as detailed below, we find not only that younger Danes have **biased** beliefs, expecting to become eligible for social security earlier than policy makers intend, but also are **highly uncertain** about eligibility age.[6] This raises concern as the welfare cost of policy uncertainty can be high

[1]For example, the European Central Bank states this explicitly: "Central bank communication has become a tool of policy in recent years. The ECB needs to be understood by markets and experts, but also by the wider public so that people can have trust in the institution and its policies." https://www.ecb.europa.eu/home/search/review/html/monpol-communication.en.html

[2]A growing body of academic literature studies the effectiveness of monetary policy communication, but the effectiveness of current communication efforts by central banks aimed at anchoring household inflation beliefs is still debated (Weber et al., 2022).

[3]The lack of deliberate communication efforts extends to other policy domains where complexity is often high. This includes tax policies and where people are left confused, e.g., Chetty and Saez (2013) and Kostøl and Myhre (2021) and benefit program take-up, e.g., Currie (2006), Finkelstein and Notowidigdo (2019), Kleven and Kopczuk (2011).

[4]Amin-Smith and Crawford (2018), Atalay and Barrett (2015), Behaghel and Blau (2012), Cribb et al. (2016), Gruber et al. (2020), Gruber and Wise (1998), Lalive et al. (2020), MacCuish (2022), Manoli and Weber (2016), Mastrobuoni (2009), Seibold (2021).

[5]The US Social Security Amendments of 1983 raised the age of eligibility for unreduced retirement benefits to 67 by the year 2027, see `https://www.ssa.gov/history/1983amend.html`

[6]Confusion about social security eligibility rules is not confined to Denmark. For example, 40% of American workers are unaware of when they will become eligible for social security benefits (`https://news.nationwide.com/americans-are-failing-in-social-security-education/`), and studies in many countries have documented widespread confusion about existing social security rules (Gustman and Steinmeier, 2005; Crawford and Tetlow, 2010; Amin-Smith and Crawford, 2018; Rohwedder and van Soest, 2006; Mastrobuoni, 2011; Liebman and Luttmer, 2015; Dolls et al., 2018.)

(Luttmer and Samwick, 2018).

The open question is how much of the gap between policy and perception is a result of communication. On the one hand, much of the gap might result from **fundamental uncertainty**: essentially unavoidable uncertainty about policy plans related to the distant future (Kosar and O'Dea, 2021, Ciani et al., 2019). Certainly in the Danish case eligibility age is a moving target. It was announced in 2006 that the transition should take place over the period 2024 and 2027, but in 2011 parliament decided to start in 2019. Moreover the policy is explicitly based on demography: every five years the age thresholds will be updated based on the development of life expectancy, with the decision to take effect 15 years later. The first revision was made in 2015 and the latest in 2020. On the other hand, some of the gap between policy plan and public perception may result from **limited awareness** and the essentially passive nature of the communication policy. The Danish government communicated the Welfare Agreement in 2006 and the revision in 2011 in press conferences. The revisions in 2015 and 2020 were again published on the home pages of the The Ministry of Employment and The Ministry of Finance, but with little fanfare.[7] Our research questions concern the extent to which **active** communication might close the gap between policy plans and perception, and whether it would do more to shift **mean** beliefs about eligibility age or to reduce **uncertainty** about eligibility age.

Again taking the lead from the tradition in monetary policy analysis,[8] we design an information treatment to address our research questions. Our treatment is particularly simple. Since the 2006 Danish reform changed only eligibility age, we randomly select half of the survey respondents and provide them with the longevity-based plan that is currently available on the official website of the Danish Ministry of Employment before asking probabilistic questions about possible eligibility age. For both treated and untreated we measure probabilistic beliefs using the "balls-in-bins" protocol of Delavande and Rohwedder (2008) which allows us to characterize the entire subjective probability distribution concerning social security eligibility and how active communication influences it.

Absent the information treatment, we find not only high uncertainty about eligibility age among workers of ages 50 and below, but also bias in expectations: they expect to become eligible for social security earlier than the published table indicates as if their beliefs have not fully adjusted.[9] The impact of the information treatment is simple and striking. **It essentially**

[7] Passive communication is not confined to Denmark. Also in the US information about social security eligibility is made available on official websites, https://www.ssa.gov/benefits/retirement/planner/agereduction.html, and people actively need to search for this information.

[8] See for example Armantier et al. (2016) and Coibion et al. (2022) for specific studies and Weber et al. (2022) and Haaland et al. (2022) for overview and other applications of information treatment designs.

[9] This is consistent with findings in other data sets. MacCuish (2022) uses ELSA to document how women subject to the UK female State Pension Reform have mistaken beliefs about their state pension eligibility age. Moreover, the finding that beliefs appear to be biased towards the old policy is consistent with a recent liter-

eliminates bias and almost completely closes the gap between statutory eligibility age and subjective mean beliefs. So it indeed appears that gaps in knowledge of current policy plans by and large account for biased beliefs. The effect of the information treatment on uncertainty is entirely different. **It has essentially no influence on subjective uncertainty**. This suggests that, unlike mean beliefs, uncertainty about future social security is largely driven by unavoidable demographic and political uncertainties.

Our information treatment not only changes beliefs about social security eligibility age, but also about expected retirement. Moreover, the gap between policy projection and subjective belief appears responsive to incentives: those who report that social security claiming age greatly impacts age of retirement have beliefs that align more closely with current projections.

How long is the information treatment retained? One might anticipate a rapid deterioration in knowledge since the treatment is so brief and there may be no immediate change in behavior for younger workers who are still decades away from claiming age. Our finding is otherwise: the information is well retained. A follow-up survey one year later shows that the effect of the information treatment in the original survey dissipates only slowly. This reveals that our simple information treatment had a durable influence on beliefs and to a large extent broke the grip of the past. Our positive results on the value of active communication highlight the need to treat such communication and allied measurement of perception as an integral part of policy design beyond the monetary policy arena.

2 Description of institutional context and the policy

Social security is universal in Denmark, i.e., it applies to all Danish citizens who are above an age threshold. It constitutes the first pillar in the pension system, where the two other pillars are occupational pensions and privately organized pensions savings accounts, see Chetty et al. (2014) for more details. Social security is pay-as-you-go funded through the tax system. The population aging and concerns about the sustainability of public spending led the parliament to decide on a major welfare reform package in 2006 (The Welfare Agreement). A key objective of this reform package was to make public finances more robust to increasing longevity and one of the specific policy initiatives was to increase the social security eligibility age and to index it to cohort specific life expectancy. The Welfare Agreement was passed through parliament in June 2006 with a majority vote of 158 out of 179, i.e., the reform package and the decision to link the eligibility age to life expectancy had very broad support.

ature showing that experience shape peoples beliefs about financial variables such as inflation and asset prices (Malmendier and Nagel, 2016, Nagel and Xu, 2021, and Malmendier and Wachter, 2021).

Table 1: *Social Security Eligibility Age by Year and Birth Cohort*

Birthdate	Eligibility Age
-31 December 1953	65.0
1 January 1954-	65.5
1 July 1954-	66.0
1 January 1955-	66.5
1 July 1955-	67.0
1 January 1963-	68.0
1 January 1967-	69.0
1 January 1971-	70.0*
1 January 1975-	71.0*
1 January 1979-	72.0*
1 January 1983-	73.0*
1 January 1987-	73.5*
1 July 1991-	74.0*
1 January 1996-	74.5*
1 July 2000-	75.0*

Notes: The social security eligibility age is set by law and will be regulated every 5 years 15 years ahead such that when life expectancy increases then the social security age will also increase. The social security ages marked with '*' are based on projections and are not yet decided by law.

The 2006 reform package and a subsequent modification in 2011 resulted in a gradual increase in the social security eligibility age by six months per year from 2019 to 2022 so as to move the social security eligibility age from 65 to 67.[10] After that, the eligibility age is indexed to the cohort specific life expectancy of 60-year-olds such that the average period where people receive social security is 19.5 years. Every five years the age thresholds will be updated based on developments in life expectancy, and the decision takes effect 15 years after. The first revision was in 2015 and the latest was in 2020. In 2021 the current social security eligibility age was 66.5 years and the parliament has now decided that the eligibility threshold will be 69 years by 2035. For cohorts born in 1971 or later the social security eligibility age is currently an estimate. Social security eligibility ages, at the time of the survey, by year and birth cohort are tabulated in Table 1.[11]

The government communicated the Welfare Agreement in 2006 and the revision in 2011 on press conferences and published the political agreement and information about the consequences of it on, among other places, the home page of the Ministry of Finance. The revisions in 2015 and 2020 were published on the home pages of the The Ministry of Employment and The Ministry of Finance. Long term projections of future social security eligibility ages were

[10] In 2006 it was originally decided that this transition should take place over the period 2024 and 2027, but in 2011 parliament decided to speed up the increase such that it started in 2019.

[11] The benefit structure was not affected by the reform. We describe the social security benefit structure in Online Appendix A.

published as early as 2006 (DREAM, 2006) and today it is straight forward to search and find the information summarized in Table 1. Direct personalized communication has never been used, but personalized information about expected pension income from all pension savings accounts as well as social security entitlements can be accessed at www.pensionsinfo.dk. However, only social security entitlements that are already decided by law are included here, i.e. at the time where we ran the survey 69 was applied as the eligibility age for all born in 1967 or later. For example, for cohorts born in 1971 or later, social security eligibility is assumed to be 69. Different communication channels thus supply different information about the consequences of the social security reform.

3 Survey and estimation

3.1 Sample

The sample invited to participate in the survey was recruited from the Danish population registry. The population registry is a complete registry of all persons who are born or have ever had an address in Denmark. It contains a personal identifier (CPR-number) applied universally to record any contact an individual has with the public sector. The CPR-number is linked to the birth date and the gender of the individual. For conducting our survey, we had access to a random sample of individuals born during the period January 1st 1951 to December 31st 2000. The survey was fielded in January-February 2021, so that invitees were between 21-70 years old at the time where the survey was completed. Invitations to participate were sent out using an official email account, called *e-boks*, which all Danes are equipped with. The survey was somewhat onerous, with many questions on past and anticipated future job transitions, conditional earnings, and private pensions, in addition to the information treatment of this paper. We collected 9,572 responses corresponding to a response rate of about 13 percent.

In January 2022 we invited all the participants from the baseline survey to participate in a follow-up survey, where we asked them about the social security eligibility beliefs in same way as we did in the baseline survey. 3,540 participated in the follow-up survey.

Within the Danish research data infrastructure it is possible to link survey responses to administrative registries. In this study, we make use of administrative data compiled by Statistics Denmark from various government agencies with information about sex, age, education, employment status, earnings, and wealth, including wealth held in retirement accounts. Currently, we have access to this information up to and including 2020. In Table A2 in Online Appendix B we display summary statistics for participants and non-participants. The table shows that participants tend to be slightly older, are more likely to have a college degree, more likely to have a job and hence have higher income. Participants also have higher wealth balances than non-participants. While these differences are statistically significant, in most cases the quantitative differences are modest. Furthermore, the standard deviations of the variables considered are quite large, reflecting a lot of heterogeneity in the sample. The pattern is similar in the follow-up survey.

3.2 Survey instruments

To elicit beliefs about future social eligibility, we ask about the probability of becoming eligible at different ages. We apply the "balls-in-bins" method proposed by Delavande and Rohwedder (2008). Specifically, we ask:

> *At what age do you expect to become eligible for social security?*
>
> *Please place all 20 balls in the bins*

Along with the question, respondents are shown a graphical representation of seven bins into which 20 balls should be distributed, by pressing a "±" button underneath the bins, such that bins with more balls represent eligibility ages that they believe are more likely. In Online Appendix C, Figure A1, we present a screen shot of the "balls-in-bins" screen.

For each respondent, i, we then estimate the mean, μ_i, and standard deviation, σ_i, of the subjective probability distribution:

$$\mu_i = \frac{1}{20}\sum_{b=1}^{20} x_{ib} \quad , \quad \sigma_i^2 = \frac{1}{20}\sum_{b=1}^{20}(x_{ib} - \mu_i)^2$$

where we assume that each ball, x_{ib}, takes the value of the midpoint of the bin.[12]

Some of the younger respondents allocated many balls to the highest bin labelled "74 or older", and the subjective probability distributions for these respondents are thus potentially censored at this point. Consequently, simple estimates of subjective means and variances may be biased downwards. To correct for this, we assume that the subjective distribution for respondents who allocated balls into the "74 or older" bin are censored at this point and that the underlying subjective distribution is symmetric and triangular. This allows us to infer means and standard deviations of the underlying uncensored distributions. In Online Appendix C we describe the

[12] Each bin is two years wide and the midpoints of bins are the odd numbers - for example, for the bin "68-69", the midpoint is 69. If a respondent believes she has a official social security eligibility age of 68, she will put her balls in bin "68-69", resulting in $\mu_i = 69$. To correct for this, for respondents with all the balls in the correct bin, we changed the values to be the correct eligibility age according to Table 1. As a robustness test, we also tried an alternative approach where we assigned each ball, x_{ib}, a random value from a uniform distribution within the boundaries of the bin, but this did not affect the results.

procedure in more detail and document that censoring of subjective distributions is concentrated at the youngest cohorts. Moreover, in the follow-up survey we included ten bins instead of seven to cover a wider age interval and thus avoid censored responses. We use the follow-up survey to validate the symmetry assumption and show that our correction procedure is appropriate.[13]

In the analysis, we also make use of additional survey instruments eliciting expected retirement age and the respondents' income and pension wealth in 2020. For these questions , beliefs are also elicited using the "balls-in-bins" method. The questions are described in detail in Online Appendix D. In the administrative data we observe third-party reported counterparts to the respondents' income and pension wealth. In Online Appendix E we directly compare the survey and third-party reported measures. The results show that survey answers match the third-party reports remarkably well. We believe this is a strong indication that survey answers are of high quality.

3.3 Information treatment

For the information treatment we randomly select half of the sample and show them Table 1 before they answer the question about beliefs about when they become eligible for social security with the following preamble:

> *The Danish Parliament decided to adjust the age at which people become eligible for social security according to when people are born, such that later born individuals qualify later for social security. This change is implemented to reflect the fact that people who are born more recently can expect to live longer. The new eligibility ages are tabulated in the table below. [Display Table 1]*

The information treatment was conducted in both the baseline survey and in the follow-up survey. In the follow-up survey, participants were randomized again so that there are four groups: never treated; treated only in baseline survey; treated only in the follow-up survey; and treated in both.

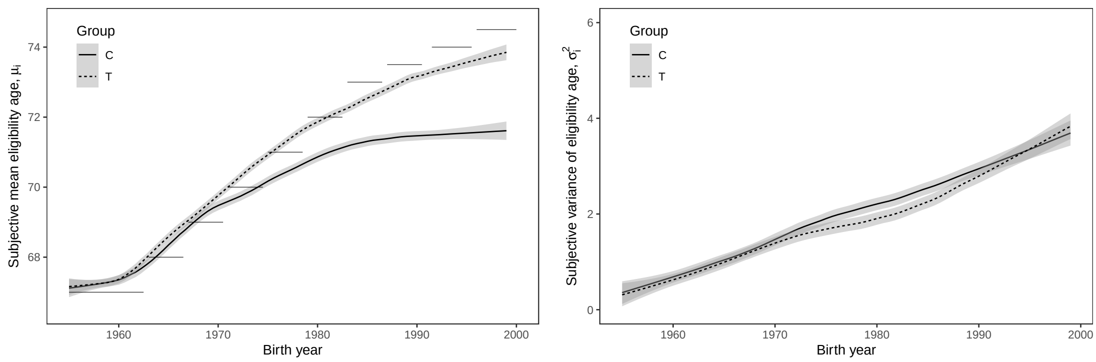
[13] In Online Appendix C we show that the subjective distributions in the follow-up survey are not skewed. This supports the use of the symmetry assumption. The subjective distributions are elicited using the "balls-in-bins" method with 20 balls. The resulting distributions are not granular enough that we can precisely determine the appropriate functional form. We therefore also implemented the correction for censoring by assuming that the underlying subjective distributions are normal. These results are reported in Online Appendix C.1, and they are for all practical purposes identical to the results based on the triangular distribution.

4 Core Results: Social Security Beliefs and Information

Figure 1 presents the core results from the baseline survey. Figure 1a shows the average subjective mean belief and Figure 1b shows the average subjective variance, i.e., subjective uncertainty. In Figure 1a official social security eligibility ages from Table 1 are illustrated with horizontal lines. The solid line shows the average subjective mean belief about social security eligibility age by birth cohorts for the control group, i.e., the group that is not information treated. The dotted line shows the corresponding line for the information treated group.

The control group is informative about the extent to which the original policy announcement has been internalized. Figure 1a shows that the average subjective mean belief, μ_i, is increasing in distance to eligibility and that the expected eligibility age is above the universal pre-reform level at 65. Cohorts born up to about 1970, on average, have mean eligibility beliefs corresponding to the age at which they actually become eligible for social security. These are the birth cohorts for whom the eligibility age has been finally decided by law. For younger cohorts, the eligibility gap, i.e., the difference between the table age and the average mean belief, widens such that eligibility beliefs are consistently smaller than the official eligibility ages listed in Table 1. The pattern for the baseline group shown in Figure 1a shows that the original policy announcement in 2006 has only partially been internalized and that the eligibility gap is higher among cohorts for whom eligibility is more distant.

Figure 1: *Social Security Eligibility Beliefs in Baseline Survey*



(a) *Average Subjective Means* **(b)** *Average Subjective Variances*

Notes: Lines show locally weighted linear regressions for control (solid) and treatment (dotted) groups for subjective mean eligibility ages, Panel 1a, and subjective variance of eligibility ages, Panel 1b. In Panel 1a horizontal lines show official eligibility ages. Fitting at point x is done locally using a neighborhood of data points around x. In all mean-plots we include 30% of all points (span = 0.3), and in all variance-plots we include 50% of all points (span = 0.5). These choices are guided by cross-validation exercises yielding optimal spans of 0.25-0.30 for mean-plots and 0.40-0.60 for variance-plots. Each point has a tricubic weight proportional to $(1 - |d|^3)^3$ where d is the distance from a given point to x scaled to $[0, 1]$ and the fit is done using least squares. The shaded areas indicate 95% point-wise confidence intervals. See Cleveland (1979) for more details.

The dotted line in Figure 1a shows the average of the subjective mean of beliefs, μ_i, for the group that was information treated. The average of mean beliefs for the treated group is closer to the official eligibility ages, indicating that the information treatment reduces the eligibility gap. The average of subjective mean beliefs tracks the official eligibility ages closely up until around cohort 1970. For younger cohorts the eligibility gap widens but is still close to the official eligibility age.[14] The fact that a simple information treatment can reduce the eligibility gap suggests that lack of knowledge about the consequences of the policy for the respondents plays a key role.

Figure 1b shows average subjective uncertainty (measured as the individual variance, σ_i^2) by birth cohort organized in the same way as Figure 1a. The solid line in Figure 1b shows that average subjective uncertainty pertaining to the belief about the social security eligibility age, is monotonically and almost linearly increasing in the birth cohort year, i.e., young people who have many years until reaching the eligibility age are more uncertain than people who are close to eligibility. The dotted line in Figure 1b shows the average subjective uncertainty for the group that was information treated. The pattern of subjective uncertainty for the treated group almost coincides with that of the control group, i.e., subjective uncertainty is not affected by the information treatment. This suggests that subjective uncertainty is driven by unavoidable fundamental policy uncertainty associated with changing demographic and political factors.

In Online Appendix G we present a model of belief formation that conceptualizes key forces that can rationalize social security belief formation. The model takes the Danish policy environment as a starting point and features a government that follows either of two potential social security policies. In one policy scenario, social security eligibility age is linked to life tables. In the other policy scenario, politicians resort to a policy with a lower eligibility age because the link to the life tables would imply too drastic an increase in the eligibility age for them to resist public pressure.[15] The two policies are common for all individuals. There is inherent uncertainty about exactly how the policies will be implemented. For example, cohort-specific life expectancy will likely be updated in the future and it is uncertain exactly how the government will implement a policy with a lower eligibility age. Individuals form subjective beliefs about their social security eligibility age by weighting the probabilities of these two underlying policies. The weighting can depend on the level of information that the individual has about the current

[14] We have also checked the robustness of the finding in Figure 1a by plotting the average share of balls allocated into the correct bin across the treatment and control groups, see Figure A6 in Online Appendix F. Reassuringly, we find that the average number of balls allocated to the correct bin is higher in the treatment group than in the control group.

[15] Such policies are in fact being discussed. As an example, an expert committee appointed by the government, the so-called Pension Commission, recently suggested that the life table indexation should be moderated such that social security eligibility indexation would only be implemented by 50 percent of the longevity differences across cohorts for cohorts born after 1975. This would, for example, imply that the cohort born in 1975 would become eligible at 70.5 and not at age 71 as specified in 1. See `https://bm.dk/arbejdsomraader/kommissioner-ekspertudvalg/kommissionen-om-tilbagetraekning-og-nedslidning`

state of the world, i.e., which policy is applicable. In that sense the model captures inattentive behavior through the weighting parameter. The information treatment mimics a policy maker sending out information that future social security eligibility ages will follow cohort specific life tables, and this may move the weight towards the life table policy as the signal informs that politicians are likely to go through with the life table policy. We develop a quantitative version of the model that is able to broadly match the average patterns of eligibility beliefs documented in this section. The quantitative model shows that the information treatment shifts the average weight from being almost entirely on the old policy to being on the new policy.

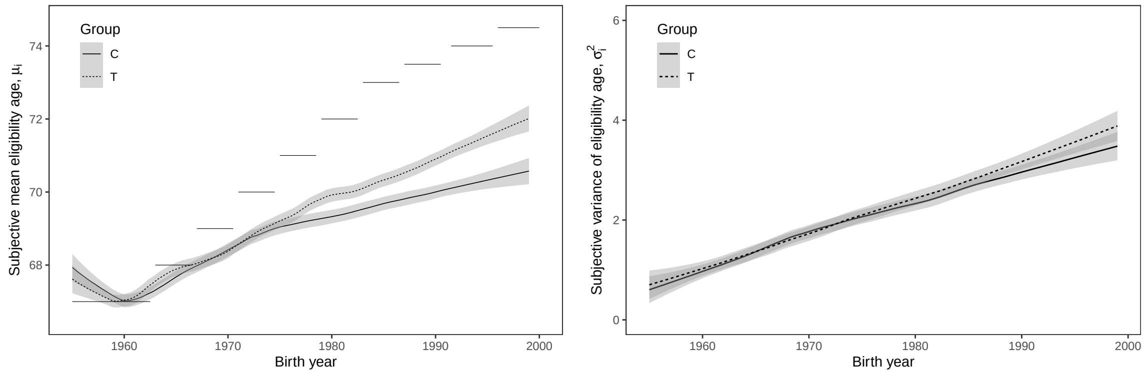
5 Retirement Plans

5.1 Social Security Beliefs, Information and Retirement Plans

Many studies have shown that retirement is sensitive to social security eligibility, i.e. retirement tend to concentrate around the point where people become eligible for social security even when incentives to retire are not very strong (e.g. Gruber and Wise, 1998; Atalay and Barrett, 2015; Seibold, 2021; Gruber et al., 2020). Hence one might expect misunderstanding of eligibilty age translates into misunderstanding of retirement age. Indeed research of Amin-Smith and Crawford (2018) and MacCuish (2022) strongly suggests that mistaken beliefs about eligibility age are predictive of the employment response upon reaching eligibility.

In the baseline survey we elicit beliefs about when the respondents expect to retire, again using the "balls-in-bins" methodology. The specific question is listed in Online Appendix D. In Figure 2 we use the answers to this question to examine how subjective beliefs about retirement vary across birth cohorts and whether the social security eligibility information treatment affects retirement plans. Panel 2a shows that mean retirement age beliefs are close to the social security age for the oldest cohorts who are close to their official social security eligibility age, but that younger cohorts consistently expect to retire before they become eligible for social security. Panel 2b shows that the subjective uncertainty about the retirement age increases almost linearly in the number of years until eligibility for social security indicating that retirement plans are, naturally, more uncertain the longer the horizon is. The information treatment shifts the mean of retirement age beliefs up for the youngest cohorts but uncertainty is left practically unaffected for all cohorts. This pattern broadly tracks the pattern documented for social security eligibility beliefs suggesting that social security beliefs do impact retirement plans.

Figure 2: *Retirement Beliefs of Treatment and Control Groups*



(a) *Average of Individual Mean Beliefs* **(b)** *Average of Individual Variance*

Notes: Lines show locally weighted linear regressions for control (solid) and treatment (dotted) groups for subjective mean eligibility ages, Panel 2a, and subjective variance of eligibility ages, Panel 2b. In Panel 2a horizontal lines show official eligibility ages. See notes to Figure 1 for details.

5.2 The Importance of Incentives

The importance of social security payments for people's retirement plans potentially depends on how much retirement savings they have and expect to accumulate until they retire. If people expect to rely more on social security payments in retirement, then they might be more attentive to changes in social security eligibility. In this section we explore whether such incentive effects are important. We do this in several steps. First, we elicit, at the individual level, how sensitive retirement plans are to changes in the social security eligibility age. We then investigate whether retirement sensitivity is correlated with expected retirement income. Finally, we explore the extent to which retirement sensitivity predicts the effect of the information treatment.

To quantify how sensitive the planned retirement age is to the age at which respondents become eligible for social security we elicit retirement beliefs conditional on being eligible for social security at age 65, the universal eligibility age before the social security reform, as well as retirement beliefs conditional on being eligible as specified in Table 1. We refer to Online Appendix D for the the exact wording of the questions. Note that these questions were posed after the information treatment so as not to provide information to the untreated.

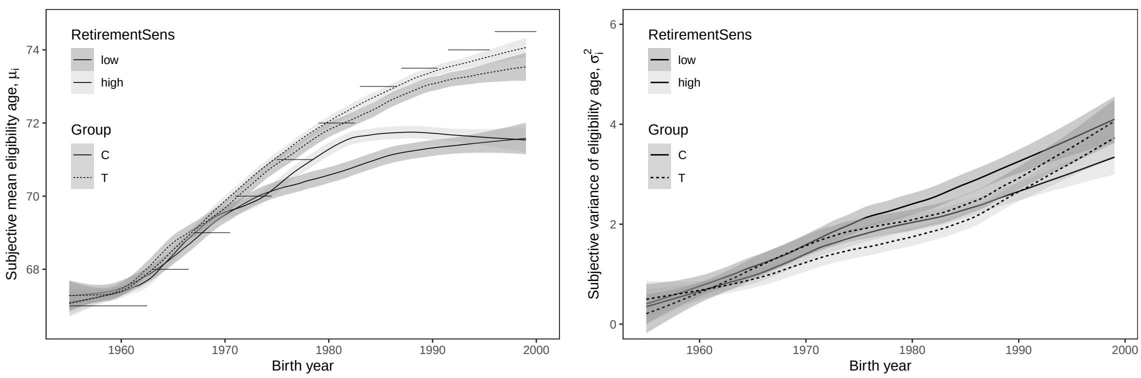
Retirement sensitivity (RS) is defined

$$RS = \frac{\mathbb{E}\left[\text{RetAge}|\text{TableAge}\right] - \mathbb{E}\left[\text{RetAge}|\text{Age65}\right]}{\text{TableAge} - 65} \tag{1}$$

RS essentially quantifies how much the mean expected retirement age is moved relative to how much the social security eligibility reform changes the social security age. We also elicit beliefs about expected retirement income arising from pension savings (see Online Appendix D). In Appendix H we show that retirement sensitivity varies with the importance of social security in retirement income. At high levels of expected retirement income, social security is relatively less important as a source of income in retirement. Consistent with this, we find that retirement sensitivity is lowest for those who expect to have a relatively high level of retirement income. This confirms that the financial incentive matters for the retirement sensitivity to the social security eligibility age

We now show how retirement sensitivity relates to beliefs about social security eligibility. We split the sample into two equally sized groups by the size of the retirement sensitivity measure, RS. The results are shown in Figure 3. We find that individuals with above-median retirement sensitivity tend to be better informed than individuals who have below-median retirement sensitivity. Still, people have downwards biased eligibility beliefs irrespective of the level of their incentive. For both groups, the information treatment shift beliefs to almost completely align with the official eligibility ages. Figure 3b shows that the information treatment has practically no effect on subjective uncertainty for both groups. These results suggests that incentives matter for information acquisition but that information frictions are important irrespective of incentives. These results resonate with the findings of MacCuish (2022). He documents that mistaken beliefs drive the decision to retire. He ascribes this to informational frictions and shows in a model of costly information acquisition how mistaken beliefs can lead retirement to be affected by the social security eligibility age.

Figure 3: *Social Security Eligibility Beliefs by above/below Median Retirement Sensitivity*



(a) *Average of Individual Mean Beliefs* **(b)** *Average of Individual Variance*

Notes: Lines show locally weighted linear regressions for control (solid) and treatment (dotted) groups for subjective mean eligibility ages, Panel 3a, and subjective variance of eligibility ages, Panel 3b. Light error bands indicate above median retirement sensitivity, dark error bands indicate below median retirement sensitivity. See notes to Figure 1. In Panel 3a horizontal lines show official eligibility ages.

5.3 Memory

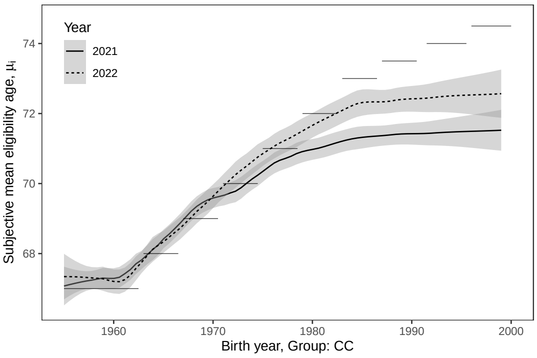
A key question is whether the information treatment has lasting effects on peoples' knowledge about when they become eligible for social security. There are reasons to be concerned that the effect will fade over time. After all, there is no obvious immediate action item for younger workers to take based on finding that their retirement will likely be delayed a few years longer than expected. Absent reinforcement, much information fades from memory. To explore this aspect, we conducted a follow-up survey in 2022, i.e., one year after the original survey, where we repeated the information treatment experiment. The resulting data show that the treatment fades only slowly in memory: much of the learning appears durable.

To demonstrate the durability of the treatment, Figure 4 shows four panels in which we plot the average beliefs about social security eligibility from the 2021 and 2022 surveys, stratified by the respondents' information treatment status in both surveys. Figure 4a shows that individuals who were neither treated in 2021 nor 2022 have similar beliefs about their social security eligibility age, in the sense that the beliefs are relatively far from the official ages. From 2021 to 2022, the beliefs are shifted slightly up.[16] Figure 4b shows beliefs for individuals who were not treated in 2021 but were treated in 2022. This panel shows that the information treatment significantly moves people's beliefs, also when the experiment is conducted within-subject. Reassuringly, Figure 4b looks similar to Figure 1a suggesting that our experimental results are not driven by selection into the survey. Figure 4c shows beliefs for individuals who were treated in both 2021 and 2022. As expected, the beliefs in the two years are practically identical and almost completely aligned with the official eligibility ages. This confirms the effectiveness of the information treatment in updating people's eligibility beliefs. Finally, in Figure 4d we show 2021 and 2022 beliefs for individuals who were treated in 2021 but not in 2022. The panel shows that social security eligibility beliefs tend to revert only slightly towards a lower social security eligibility age in 2022. This suggest that respondents clearly remember the treatment after one year, While memory does appear to decay, it does so only slowly. A large portion of the de-biasing effect of the information treatment is retained for at least a year.[17]

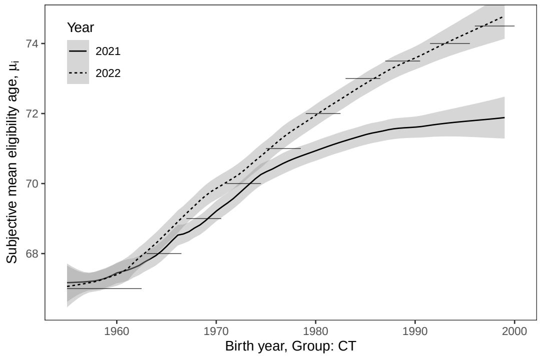
[16] This may either reflect general learning or more specifically that participation in the 2021 survey induced people to acquire more information about social security rules.

[17] The corresponding figures for the subjective variances are shown in Online Appendix I.

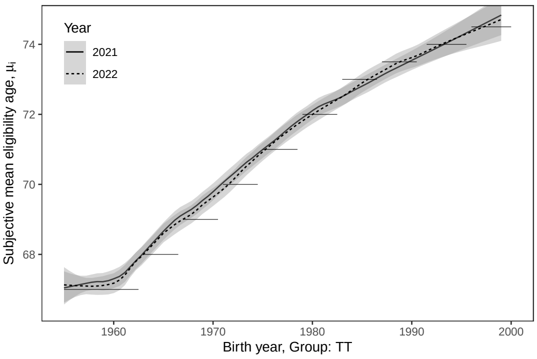
Figure 4: *Follow-Up Survey by Treatment Status in 2021/2022, Mean*



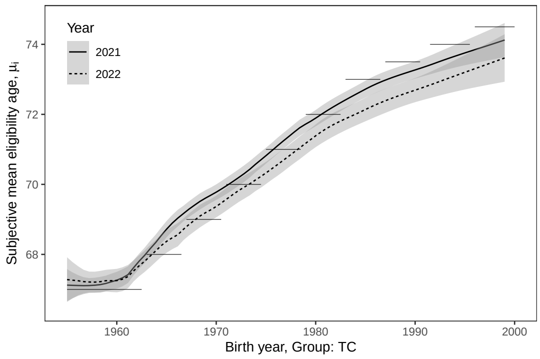
(a) *Control-Control*



(b) *Control-Treatment*



(c) *Treatment-Treatment*



(d) *Treatment-Control*

Notes: Lines show locally weighted linear regressions for subjective mean eligibility ages for 2021 survey (solid) and 2022 survey (dotted). The panels show each combination of control and treatment in the 2021 and the 2022 survey. Results are only for the 3,540 respondents who participated in both surveys. The horizontal lines show official eligibility ages. See notes to Figure 1 for details.

6 Conclusion

Policy communication is rarely an integral part of policy design, except when it comes to monetary policy. Social security is a case in point. Social security reform is being implemented across the world, but widespread uncertainty has been documented in county after country.

We study a Danish 2006 reform that replaced universal social security eligibility at age 65 with longevity-based eligibility. We measure probabilistic beliefs about eligibility age for a large sample of Danes. To assess the role of policy communication we implement a simple information treatment in which we randomly provide survey respondents access to the currently planned longevity-based eligibility age reform. Absent the information treatment, we find that younger workers not only expect to become eligible for social security earlier than the published table, but also are highly uncertain about eligibility. The information treatment essentially eliminates the gap in expectations, suggesting it results from misunderstanding. Yet it has essentially no influence on subjective uncertainty, suggesting that this is driven by unavoidable demographic and political uncertainties.

Our results highlight the importance of incorporating communication strategies, including belief measurement and information treatments, into policy design outside the monetary policy arena.

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Appendix

to

Communicating Social Security Reform

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A Social Security Benefits in Denmark

The policy investigated in this paper changed the eligibility age, but did not affect the benefits conditional on being eligible, i.e., the benefit structure was unaffected by the policy change. Social security benefits consist of a basic benefit and a supplement.

Table A1: *Yearly Social Security Benefits (DKK), 2021*

	Single	In couple
Basic	78,216	78,216
Supplement	88,022	44,484
Total	166,238	122,700

The basic benefit is awarded to everyone who are eligible to social security benefits subject to not having earned income above a threshold. The basic social security benefit is tested against earnings such that benefits are reduced with 30 percent of the income above 344,600 DKK. This means that no social security benefits are paid out if earned income exceeds 605,300 DKK per year. Payments from pension schemes (be it private or labor market pension schemes) have no impact on the basic benefits.

The supplement is tested against household taxable income net of social pensions, including income from retirement accounts and income of the spouse. The supplement is reduced by 32 percent of (household) income exceeding a threshold. The threshold is 76,100 DKK for singles and 152,500 DKK for couples.

Social Security can be postponed with a bonus. For every two months that benefit payments are postponed a bonus of 1 percent is earned, meaning that payments will be 1 percent higher when benefit payments begin and will remain 1 percent higher for the remaining life time. It is possible to postpone benefit payments for up to ten years after which the benefit level will be 160 percent of the basic rate.

B Summary Statistics

Table A2: *Balance Table*

	Baseline survey 2021			*Follow-up survey 2022*		
	Participants	Non-participants	Difference	Participants	Non-participants	Difference
female	0.492	0.493	-0.001	0.476	0.502	-0.026
	(0.5)	(0.5)	(0.006)	(0.499)	(0.5)	(0.011)
age	48.389	43.601	4.788	52.68	47.472	5.208
	(12.179)	(12.8)	(0.135)	(11.218)	(12.308)	(0.248)
college	0.488	0.341	0.148	0.501	0.481	0.021
	(0.5)	(0.474)	(0.005)	(0.5)	(0.5)	(0.011)
employed	0.842	0.785	0.057	0.839	0.844	-0.004
	(0.365)	(0.411)	(0.004)	(0.367)	(0.363)	(0.008)
earnings	408,197	325,309	82,888	428,503	396,367	32,136
	(311,201)	(311,782)	(3,431)	(335,858)	(295,277)	(6,842)
wealth	443,926	248,848	195,078	519,329	399,997	119,331
	(4,792,147)	(2,620,078)	(50,299)	(1,673,064)	(5,891,539)	(81,160)
pension	1,579,293	993,810	585,483	1,894,543	1,395,629	498,914
	(1,874,468)	(1,490,113)	(20,150)	(1,944,205)	(1,807,606)	(40,326)
N	9,572	62,594		3,540	6,032	

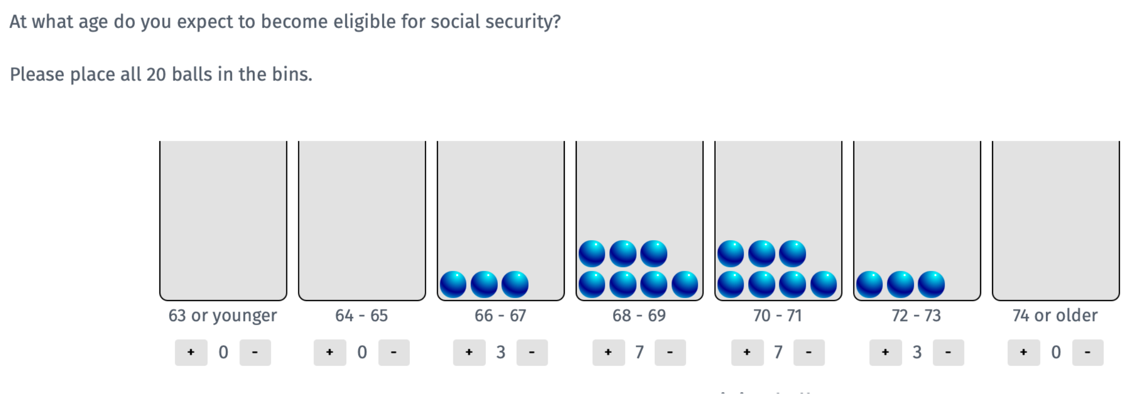
Table A3: *Tabulation of observations by social security eligibility age*

	Baseline survey 2021		*Follow-up survey 2022*			
Eligibility age	Control	Treatment	CC	CT	TC	TT
67.00	1,248	1,297	313	319	320	298
68.00	614	591	152	131	136	126
69.00	586	520	142	104	108	95
70.00	496	488	94	79	79	80
71.00	384	421	62	48	69	63
72.00	331	344	43	53	48	43
73.00	293	322	38	43	43	49
73.50	306	318	30	40	39	29
74.00	289	263	30	26	33	28
74.50	227	234	32	28	25	22

C The "Balls-in-Bins" Survey Instrument

Figure A1 show the graphical "balls-in-bins" interface that respondents meet in the survey. Along with the question, respondents are shown a graphical representation of seven bins into which 20 balls should be distributed, by pressing a "±" button underneath the bins, such that bins with more balls represent eligibility ages that they believe are more likely.

Figure A1: *"Balls-in-Bins"*



Notes: The graphical user interface where the respondents place 20 balls in seven bins to reflect their subjective beliefs.

Some respondents allocated many balls into the bin labelled "74 or older". The elicited subjective distribution, for respondents who associate substantial mass to this category, thus become censored, i.e. exhibit excess mass, at this category. To correct for this, we impose an underlying symmetric triangular distribution for respondents with balls in the category "74 or older" such that the adjusted distribution extends into age categories not specified explicitly in Figure A1[1].

The procedure is illustrated with an example in Figure A2. The top panel illustrates one such individual response where balls have been allocated to the bin "74 or older". In the middle panel, we take all the balls in the lower bins with a minimum value a and maximum value a', and consider the triangle with height h and area γ (the fraction of balls in lower bins). The height of the triangle is $h = \frac{2\gamma}{a'-a}$, and the probability density function of the symmetric triangular distribution is:

$$h = \frac{x-a}{(c-a)^2}.$$

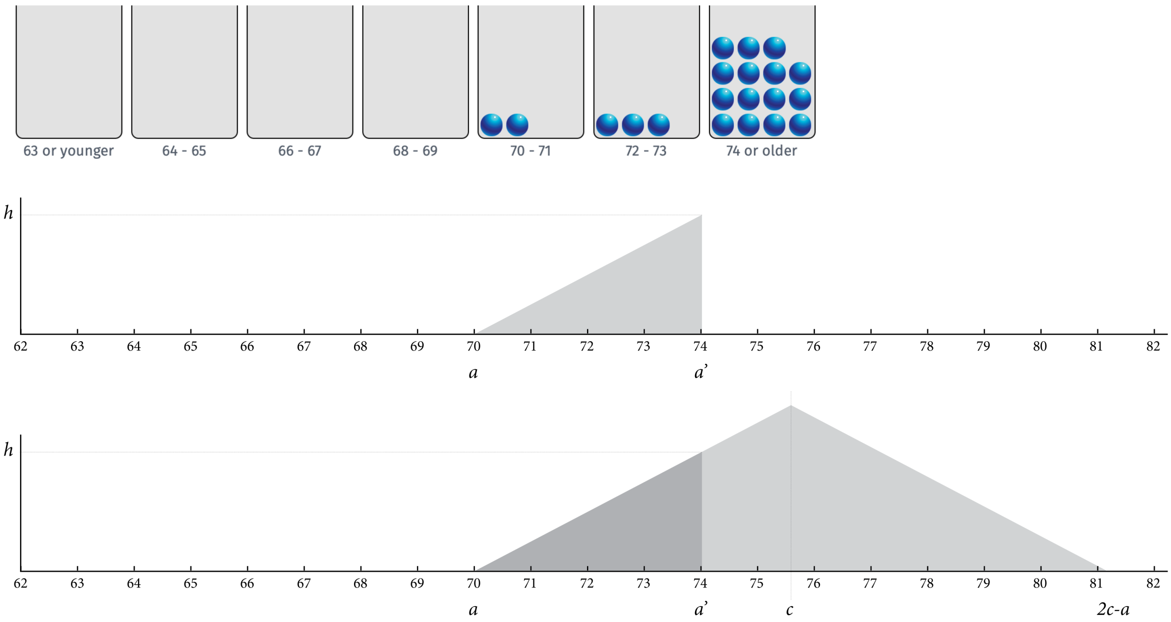
Solving for the peak value, c, gives

$$c = \sqrt{\frac{x-a}{h}} + a$$

[1]We can only impose the triangular distribution for respondents who, in addition to having balls in the category "74 or older" also have balls in at least one of the other categories, as these balls guide the parameters of the imputed triangular distribution.

which uniquely identifies the distribution. The bottom panel of Figure A2 shows how the imposed distribution looks.

Figure A2: *"Balls-in-Bins", imposing a triangular distribution*



Notes: The "balls-in-bins" instrument has a cap at "74 or older". For distributions where "74 or older" has at least one ball, we impose a triangular distribution. The top panel shows an example distribution, the middle panel shows the triangle used to infer the underlying distribution, and the bottom panel shows the underlying distribution.

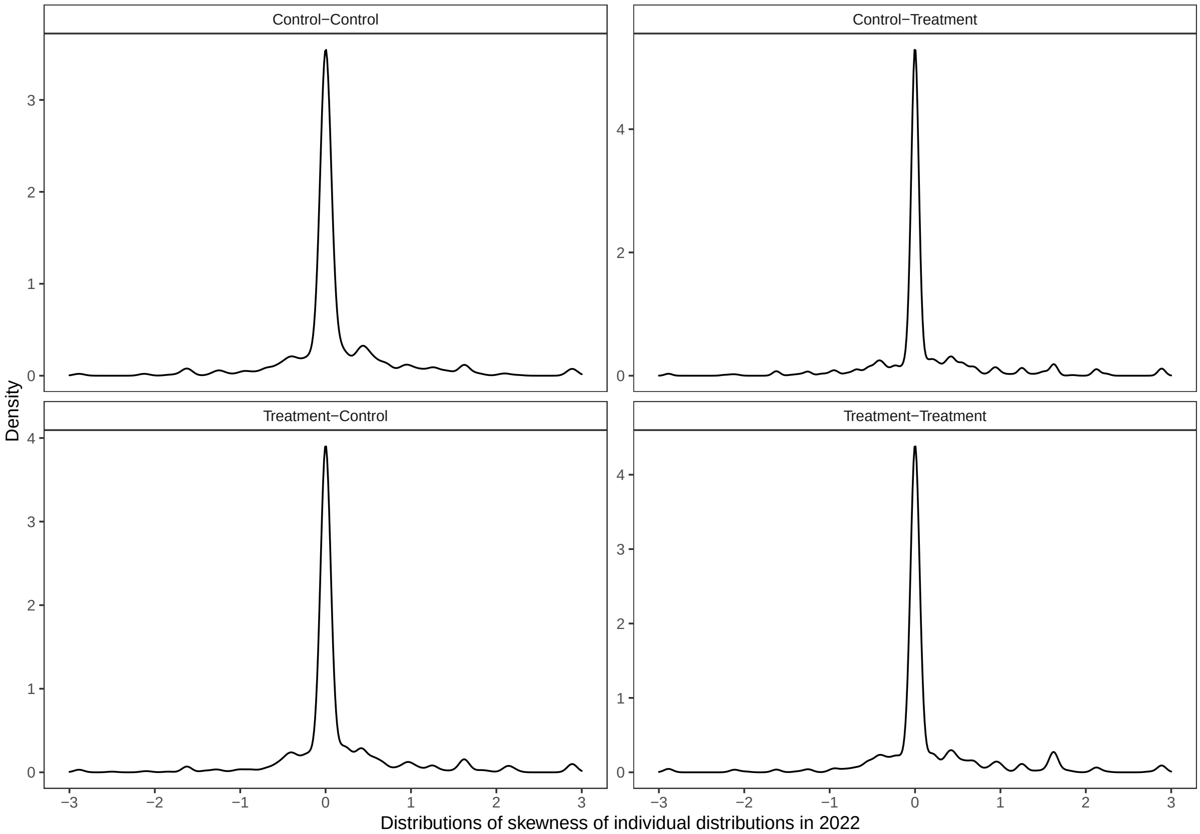
The censoring problem naturally affects younger cohorts the most. In Table A4 the fraction of responses that we have corrected is listed.

Table A4: *Fraction of observations within each cohort group on which symmetry is imposed*

Eligibility age	Fraction with imposed triangular distribution
67.00	0.02
68.00	0.04
69.00	0.08
70.00	0.17
71.00	0.28
72.00	0.38
73.00	0.44
73.50	0.51
74.00	0.52
74.50	0.53

The procedure assumes two features of the distributions: Symmetry and functional form. We test the symmetry assumption using answers from the follow-up survey, where we allowed for a wider support. Specifically, we allowed for three additional 2-year age bins such that the possible age categories span from "63 or younger" to "80 or older". In this way, the subjective distributions are in practice uncensored. In Figure A3 we plot the density of individual skewness by treatment status in both 2021 and 2022. It shows that skewness is heavily centered around zero and 87% of individual distributions have an absolute skewness below one. This show that it is reasonable to assume that subjective distributions tend to be symmetric.

Figure A3: *Distribution of Subjective Skewness by 2021-2022 Treatment Status*



Notes: Distribution of subjective skewness in 2022 for respondents by treatment status in 2021 and 2022.

C.1 Correcting for Censoring using a Gaussian Distribution

In the main analysis we impute impute uncensored subjective distributions by assuming that the underlying distributions are triangular. To examine the robustness of this, we also implement the procedure assuming that the underlying uncensored distribution is Gaussian. Following **?** we use the fraction of balls, γ, located in bins lower than the cut-off, $a = 74$ (all except "74 or older"), and calculate the quantile function of γ (the inverse of the cumulative distribution function for a Gaussian distribution):

$$\alpha = \Phi^{-1}(\gamma)$$

We then calculate the auxiliary variable, λ, (where ϕ is the Gaussian probability density function):

$$\lambda = \frac{\phi(\alpha)}{\gamma}$$

The mean of the truncated distribution is given by (**?**):

$$\mathbb{E}[x|x < a] = \mu + \lambda\sigma$$

and

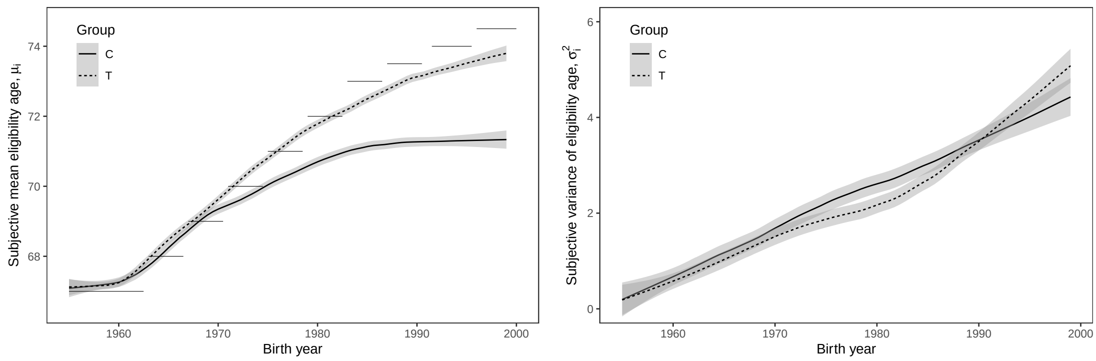
$$\alpha = \frac{a - \mu}{\sigma}$$

This can be arranged in a system of linear equations:

$$\begin{bmatrix} \mu & \lambda\sigma \\ \mu & \alpha\sigma \end{bmatrix} = \begin{bmatrix} \mathbb{E}[x|x < a] \\ a \end{bmatrix}$$

Solving these yield the parameters of the underlying distribution, μ and σ. Figure A4 shows the results. The results are practically identical to the case where we use the triangular distribution.

Figure A4: *Social Security Eligibility Beliefs in Baseline Survey. Imputed Gaussian distribution for censored 2021 answers*



(a) *Average Subjective Means* **(b)** *Average Subjective Variances*

Notes: Lines show locally weighted linear regressions for control (solid) and treatment (dotted) groups for subjective mean eligibility ages, Panel A4a, and subjective variance of eligibility ages, Panel A4b. Censored distributions are imputed assuming a Gaussian distribution. See notes to Figure **??**. In Panel A4a horizontal lines show official eligibility ages.

D Additional Survey Instruments

The questions listed below were only asked in the 2021 survey

Income 2020

What was your earned income during 2020?

Please report the most accurate value you can:

Retirement wealth 2020

Consider how much wealth you have accumulated in total in pension accounts by now.

Please report your belief about this accumulated amount.

Lowest possible amount:

Highest possible amount:

Please enter all 20 balls in the bins

Retirement I

How old do you expect to be when you retire?

Please consider the various factors that are uncertain and that may affect your retirement age (for example, health, savings, or other factors that may be important).

Please enter all 20 balls in the bins

Retirement II

Suppose that you first become eligible for social security at the age of 65.

At what age do you expect to retire?

Please enter all 20 balls in the bins

Retirement III

Suppose that you first become eligible for social security at the age of [Table age]. At what age do you expect to retire?

Please enter all 20 balls in the bins

Income from Pension Wealth

Suppose you retire at age [Table age], and suppose you stay in your current job until retirement.

How much annual income in retirement do you believe your pension would provide?

Lowest possible amount:

Highest possible amount:

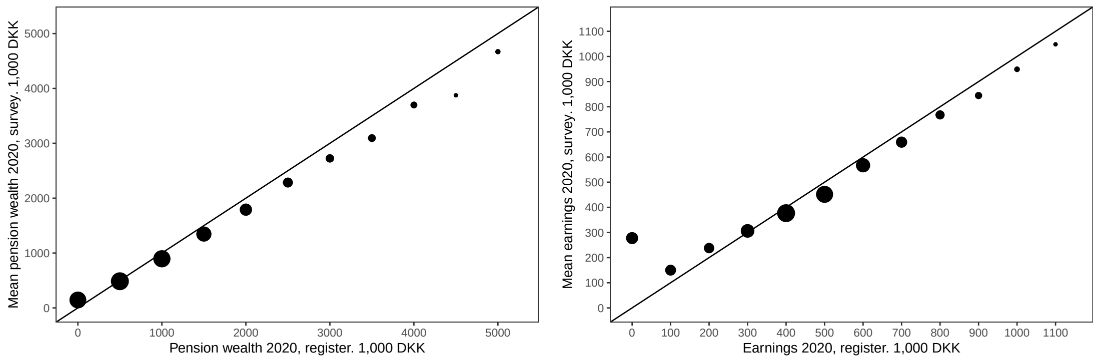
Please enter all 20 balls in the bins

E Validation

An important question is whether respondents are able and willing to respond accurately to the questions that they are asked in the survey. To assess this we asked the respondents about pension wealth and earnings in 2020 and we then compare stated pension wealth and earnings from the survey with their third-party reported counterparts from the administrative registers. Figure A5a reports average pension wealth as reported in the survey in 2020 by DKK500,000 bins of pension wealth as recorded in the administrative register for 2020. Panel A5b reports average earnings as reported in the survey in 2020 by DKK100,000 bins of earnings as it is recorded in the administrative register data for 2020. In both panels, the size of the dots indicate number of observations and the dotted line is a weighted OLS regression through the micro data with coefficients reported in the top-left of the panel.

The reported pension wealth is very close to the 45-degree line. Reported earnings is also close to the 45-degree line, except at the bottom end of the 2018 distribution. Overall, Figure A5 shows that survey responses align remarkably well with objective third-party reported measures from the administrative register data. These findings confirm that respondents are able and willing to provide meaningful answers in the survey.

Figure A5: *Validation of Survey Responses*



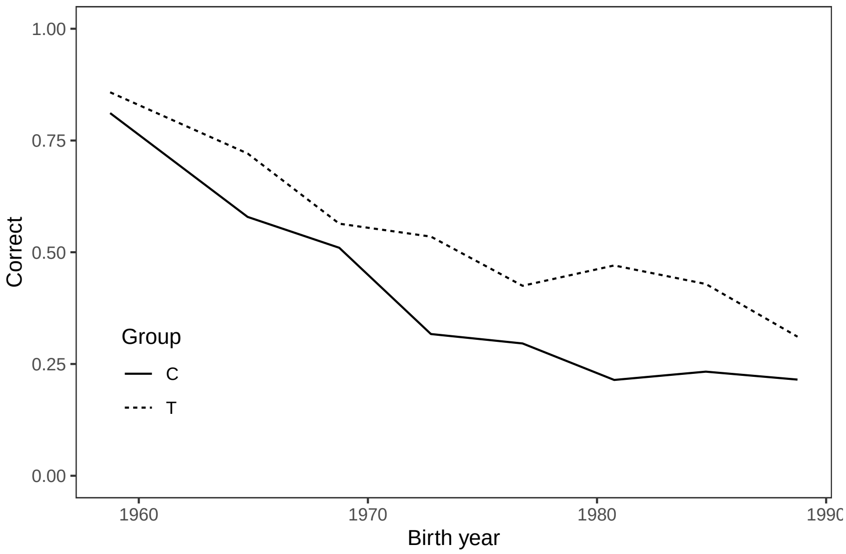
(a) *Mean reported pension savings, 2020*

(b) *Mean reported earnings, 2020*

Notes: The figure shows the relationship between reported pension wealth, Panel A5a, (earnings, Panel A5b) in 2020 against the corresponding measure that is third-party reported in the administrative register in 2020. The panels show binned scatter plots (black circles) where the bins are defined over intervals of the register measure. The size of the dots is proportional to the number of observations in the bin. The 45 line is overlaid.

F Robustness

Figure A6: *Fraction of Balls in Correct Bin 2021*



Notes: The figure shows the fraction of balls allocated into the correct bin for the information treated group and the control group in the baseline survey 2021.

G A Model of Policy Beliefs

In this Appendix we formulate a model of belief formation that conceptualizes the key forces that drive social security belief formation, and develop a quantitative version of it that is able to broadly match the average patterns of eligibility beliefs documented in section **??**.

The model takes the Danish policy environment as a starting point. The government follows either of two potential social security policies. In one policy scenario, social security eligibility age is linked to life tables. In the other policy scenario, politicians resort to a policy with a lower eligibility age because the link to the life tables would imply too drastic increases in the eligibility age for them to resist public pressure. The two policies are common for all individuals. There is inherent uncertainty about exactly how the policies will be implemented. For example, cohort-specific life expectancy will likely be updated in the future and it is uncertain exactly how the government will implement a policy with a lower eligibility age. Individuals form subjective beliefs about their social security eligibility age by weighting the probabilities of these two underlying policies. The information treatment mimics a policy maker sending out information that future social security eligibility ages will follow cohort specific life tables, and this may move the weight towards the life table policy as the signal informs the individual that politicians are likely to go through with the life table policy.

To formalize this, denote the life table policy as policy $q = 1$ and the alternative policy as policy $q = 2$ and assume that the eligibility age under either policy is characterized by a normal distribution capturing the underlying uncertainty: $f_{q,k} \sim N(\mu_{q,k}, \sigma^2_{q,k})$ where $q = 1, 2$, and k is an indicator for the cohort group, c.f., Table **??**. The subjective beliefs about eligibility age, f, is given by the mixture of the two normal distributions

$$f_{1,k} \sim N(\mu_{1,k}, \sigma^2_{1,k}) \tag{1}$$

$$f_{2,k} \sim N(\mu_{2,k}, \sigma^2_{2,k}) \tag{2}$$

$$f_{k,D} = p_{k,D} f_{1,k} + (1 - p_{k,D}) f_{2,k} \tag{3}$$

The parameters of $f_{q,k}$ need not be the same across cohort groups, but by randomization, they are identical across treatment and control groups. $f_{k,D}$ is the average subjective distribution at time t for individuals belonging to cohort group[2] k with treatment status D, where $D = T$ when information treated and C otherwise. $p_{k,D}$ is the average subjective weight on policy 1, the life table policy for cohort group k with treatment status D. The mean and variance of $f_{k,D}$ has the following closed form solution:

$$m_{k,D} = \mathbb{E}[f] = p_{k,D}\mu_{1,k} + (1 - p_{k,D})\mu_{2,k} \tag{4}$$

$$s^2_{k,D} = \mathbb{V}[f] = p_{k,D}\sigma^2_{1,k} + (1 - p_{k,D})\sigma^2_{2,k} + p_{k,D}(1 - p_{k,D})\left(\mu_{1,k} - \mu_{2,k}\right)^2 \tag{5}$$

The first two terms of Equation (5) are the weighted variances of the underlying distributions and the third reflects the added variance coming from the distance between the means of the underlying distributions. The behavioral parameter of interest is the subjective probability weight on the life table policy, $p_{k,D}$. We fit the parameters of the model and estimate how the information treatment works through $p_{k,D}$.

G.1 Fitting the Model

The model has six parameters for each cohort group, $p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma^2_{1,k}, \mu_{2,k}, \sigma^2_{2,k}$. From the elicited distributions we use four empirical moments: average subjective means and variances for both the treatment and the control group, i.e., $\bar{m}_{k,T}$, $\bar{s}^2_{k,T}$, $\bar{m}_{k,C}$, and $\bar{s}^2_{k,C}$ for all cohort groups, k. With six parameters and four empirical moments, the model is not identified and we need to impose some additional restrictions. The restrictions we impose follow naturally from the policy environment. First, we fix $\mu_{1,k}$, the mean of the life table policy, to take the values listed

[2] We use cohort groups that correspond to the eligibility ages, c.f., Table **??**. The data used to fit the model is cohort group specific average moments.

in Table ??. Next, we assume that $\sigma^2_{1,k} \geq \sigma^2_{1,k-1}$, i.e., that uncertainty about the life table is at least as big for cohort k as it is for cohort $k-1$. This is essentially just saying that young cohorts face at least as much uncertainty as older cohorts, meaning that life expectancy is at least as hard to predict for the young as for the old because of the longer horizon. Similarly, we assume that $\sigma^2_{2,k} \geq \sigma^2_{2,k-1}$ because a long horizon leaves at least as much uncertainty about the details of a future alternative policy. Finally, we restrict $\mu_{2,k} \in \left[\overline{\min(m_{k,C})}, \mu_{1,k}\right]$ where $\overline{\min(m_{k,C})}$ is the average of the minimum possible eligibility age indicated by control group individuals in their "balls-in-bins" answer to the question about their social security eligibility age, setting a lower limit, and $\mu_{1,k}$ is the table age. We fit the six parameters by minimizing the squared distance between the empirical moments, $\bar{m}_{k,C}$, $\bar{m}_{k,T}$, $\bar{s}^2_{k,C}$, $\bar{s}^2_{k,T}$, and the corresponding model implied moments, cf., equations (4) and (5).[3]

G.2 Minimum Distance

The model has six parameters for each cohort, $p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma^2_{1,k}, \mu_{2,k}, \sigma^2_{2,k}$. We observe average subjective means and variances, i.e., $\bar{m}_{k,C}$, $\bar{m}_{k,T}$, $\bar{s}^2_{k,C}$, and $\bar{s}^2_{k,T}$ for all the cohort groups and for the treatment and control groups. In order to identify the model parameters, we thus need to impose some additional restrictions. First, we fix $\mu_{2,k}$, the mean of the life table policy, to take the value listed in Table ??. Next, we assume that $\sigma^2_{2,k} \geq \sigma^2_{2,k-1}$ and $\sigma^1_{2,k} \geq \sigma^1_{2,k-1}$. Finally, we restrict $\mu_{1,k} \in \left[\overline{\min(m_{k,C})}, \mu_{2,k}\right]$ where $\overline{\min(m_{k,C})}$ is the average of the minimum possible eligibility age indicated by control group individuals in their "balls-in-bins" answer to the question about their social security eligibility age, and $\mu_{2,k}$ is the table age. We find the values of the parameters, $p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma^2_{1,k}, \sigma^2_{2,k}$ by minimizing the squared distance between the empirical moments, $\bar{m}_{k,C}$, $\bar{m}_{k,T}$, $\bar{s}^2_{k,C}$, and $\bar{s}^2_{k,T}$, and the corresponding model implied moments in equations (4) and (5) subject to the constraints listed above and separately for each cohort. This is summarized in equation (6):

$$\Theta = \underset{p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma^2_{1,k}, \sigma^2_{2,k}}{\operatorname{argmin}} \left[(m_{k,C} - \bar{m}_{k,C})^2 + (m_{k,T} - \bar{m}_{k,T})^2 + (s^2_{k,C} - \bar{s}^2_{k,C})^2 + (s^2_{k,T} - \bar{s}^2_{k,T})^2\right]$$

subject to

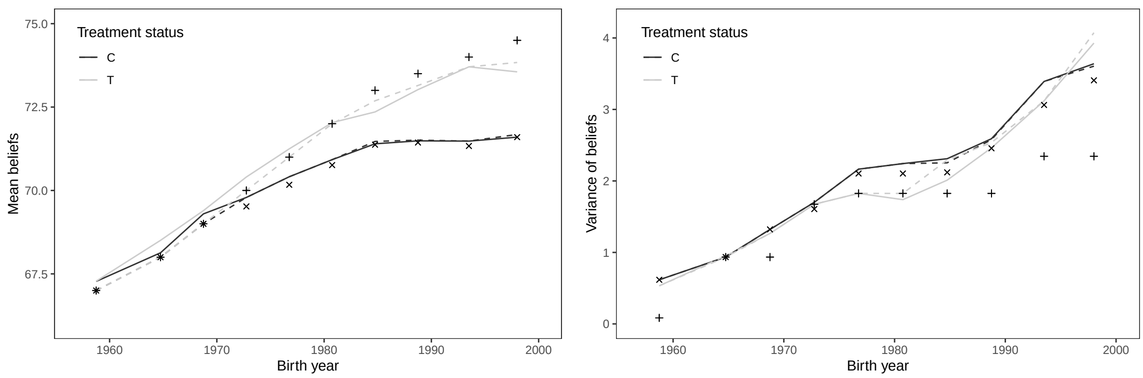
$$\begin{aligned} &\sigma^1_{2,k} \geq \sigma^1_{2,k-1} \\ &\sigma^2_{2,k} \geq \sigma^2_{2,k-1} \\ &\mu_{1,k} \in \left[\overline{\min(m_{k,C})}, \mu_{2,k}\right] \end{aligned} \tag{6}$$

[3]We refer to Appendix G.2 for details about the minimum distance procedure.

G.3 Results

In Figure A7 we report the model's ability to replicate average mean beliefs, Panel A7a, and uncertainty, Panel A7b, by information treatment status. Panel A7a shows average beliefs in the data with solid lines and model generated mean beliefs with dashed lines. The model implied mean beliefs match the data quite closely for both the treatment and the control group and for all cohorts. Moreover, the fitted model is able to replicate the effect of the information treatment. Panel A7b shows average subjective uncertainty in the data with solid lines and model implied subjective uncertainty with dashed lines. Also here there is a close correspondence between data and model implied average beliefs where average subjective uncertainty is increasing in cohort year and with no effect of the information treatment. The fact that there is no effect of treatment on the average subjective uncertainty reflects that the overall subjective uncertainty is affected by the difference in mean eligibility ages between the two policy distributions as well as by the uncertainty associated with each of the underlying policy components, cf. equation (5). Subjective uncertainty thus reflects inherent policy uncertainty associated with both policy regimes.

Figure A7: *Estimated model parameters*

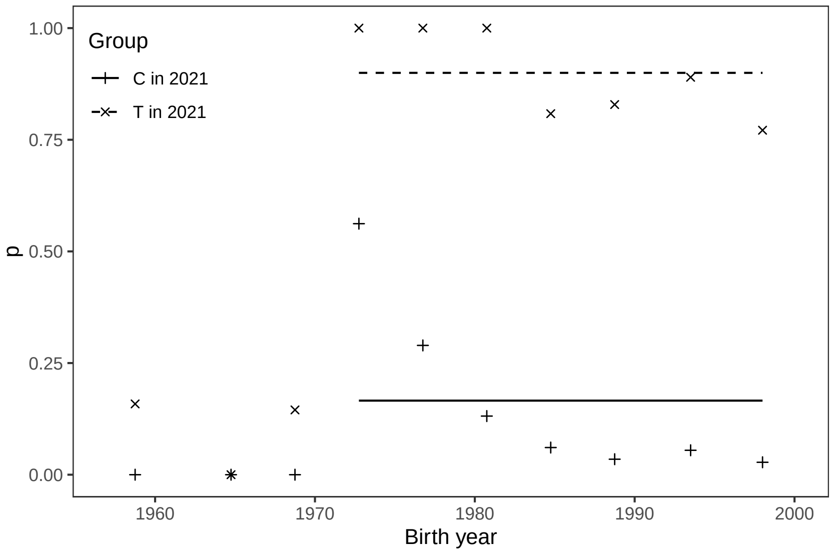


(a) *Mean fit* **(b)** *Variance fit*

Notes: Panels A7a and A7b show the results from fitting Equations (4) and (5) to average subjective means, Panel A7a, and variances, Panel A7b, separately for all cohort groups and for treated and untreated individuals. Solid lines are data moments and dashed lines are fitted values. In Panel A7a, '+'s indicate $\mu_{1,k}$, which is fixed to match official eligibility ages listed in Table **??**, and '×'s are fitted values of $\mu_{2,k}$. In Panel A7b, '+'s are fitted values of $\sigma^2_{1,k}$ and '×'s are fitted values of $\sigma^2_{2,k}$.

In the model described by Equations (4) and (5) the effect of the information treatment operates through shifting the subjective weight on the life table policy, $p_{k,D}$. In Figure A8 we plot with '+'s and '×'s the estimates of $p_{k,D}$ for $D = (C, T)$, i.e., for the control and treatment groups for all cohort groups. For the three oldest cohort groups, $p_{k,D}$ is not identified as there is no discernible difference between the beliefs of the treatment and control groups. The weights are approximately constant across cohorts within the treatment and control groups as indicated by the horizontal lines. For the control group, the average weight put on the life table policy is 0.17, compared to 0.90 for the treatment group. This means that the treatment induces a large increase in the weight assigned to the life table policy, $p_{k,D}$. In other words, the information treatment is extremely successful in shifting the average subjective weight from the alternative policy to the life table policy, such that people who have been information treated predominantly form their beliefs based on the life table policy scenario.

Figure A8: *Fitted model weights*

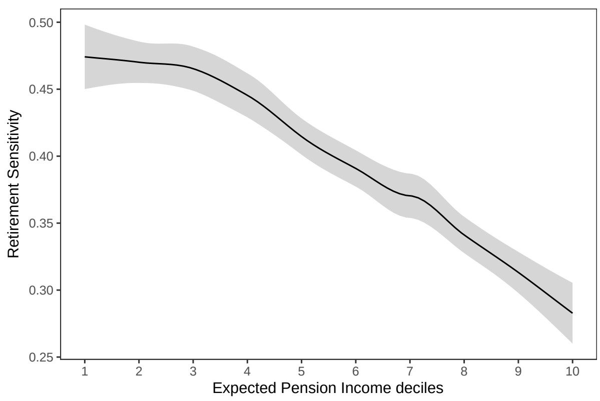


Notes: Fitted values of the weight on the life table policy, $p_{k,D}$, for $D = (C, T)$, i.e., for the control and treatment groups, for all cohort groups, k. Mean values for all but the three oldest cohort groups are overlaid. For the oldest cohort groups, $p_{k,D}$ is not identified as there is no discernible difference between the beliefs of the treatment and control groups. Figure A7 shows the fit of the four moments of the common underlying distributions, $f_{q,k}$.

H Incentives

Figure A9 shows how retirement sensitivity varies with the importance of social security in retirement income. It plots retirement sensitivity, RS, as defined in equation (**??**), against deciles of expected retirement income. At high levels of expected retirement income, social security is relatively less important as a source of income in retirement, i.e., the financial incentive provided by social security is smaller the higher is expected retirement income. The figure shows that retirement sensitivity is negatively correlated with the expected retirement income level. This confirms that the financial incentive matters for the retirement sensitivity to the social security eligibility age.

Figure A9: *Pension income, deciles*

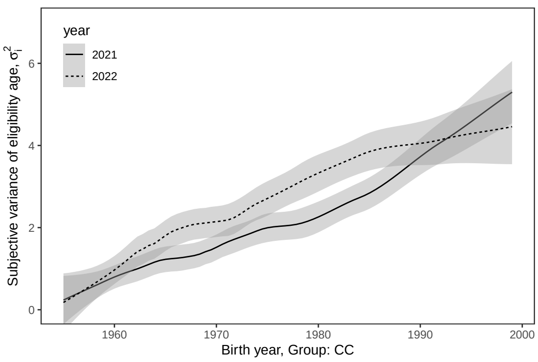


Notes: The figure shows a locally weighted linear regression for the relationship between retirement sensitivity (c.f., equation (**??**)) and deciles of expected pension income. See notes to Figure **??**.

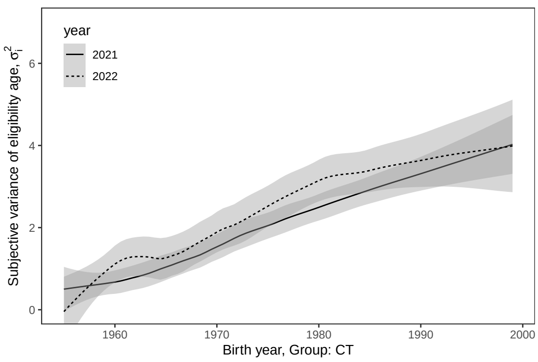
I Further Evidence from the Follow-Up Survey

In Figure A10 we show the average subjective variances of social security eligibility ages from the follow-up survey, where the panels are organized in the same way as in Figure **??**. The samples underlying the panels in Figure A10 are much smaller than in the baseline survey in 2021 and the relationships are therefore less precisely estimated. In all panels the average of subjective uncertainty is increasing in distance to eligibility and thus display the same behavior as in Figure **??**. Generally there appears to be no effect of the information treatment, albeit in Figure A10d, showing the variances for the group that was information treated in 2021, but not in 2022, the variance appears to increase for younger cohorts going from 2021 to 2022.

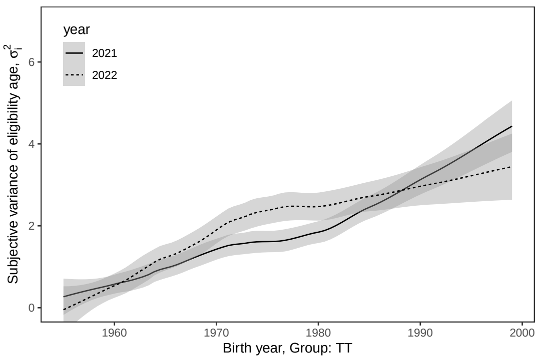
Figure A10: *Follow-Up Survey by Treatment Status in 2021/2022, Variance*



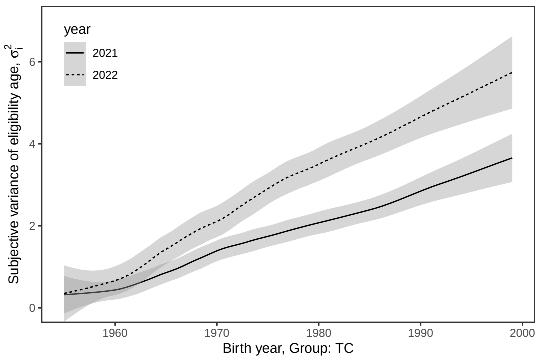
(a) *Control-Control*



(b) *Control-Treatment*



(c) *Treatment-Treatment*



(d) *Treatment-Control*

Notes: Lines show locally weighted linear regressions for subjective variances of eligibility ages for 2021 survey (solid) and 2022 survey (dotted). The panels show each combination of control and treatment in the 2021 and the 2022 survey. Results are only for the 3,540 respondents who participated in both surveys.See notes to Figure **??** for details.