COMMUNICATING SOCIAL SECURITY REFORM

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Abstract

Despite its centrality in monetary policy design, policy communication is not a focus in other important areas, such as social security reform. Might improved communication lower the widespread confusion about the future of social security that has been identified worldwide? To answer this question we implement a simple information treatment in Denmark which in 2006 replaced universal social security eligibility at age 65 with longevity-based eligibility. We measure probabilistic beliefs about eligibility age both with and without this treatment, which is strikingly simple: we actively communicate the longevity-based plan as currently available on the official Website. We find that treatment essentially removes anchoring in the past. Average beliefs of those who are treated are significantly different of those who are not, and align well with current policy plans. Our results implicate poor communication as a primary source of confusion and highlight the widespread need to treat communication strategies as integral to policy.

Keywords: social security, belief updating, information treatment, policy uncertainty

JEL codes: D8, H55, J26

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1 Introduction

When people have limited information processing capacity, policy makers cannot assume that the public know about the policy just because it is announced. Simple and salient communication is required to make people pay attention and avoid that they forget quickly (Sims, 2010). This has been adopted by monetary policy makers, and communication is now an integral part of monetary policy design.\(^1\) Central banks announce inflation targets and their plans for achieving them in the form of ‘forward guidance’. Communication strategies are designed to provide policy information in a digestible manner and thereby reduce both misunderstanding and uncertainty about future policy. 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.\(^2\)

In contrast, communication is not a focus in other important policy areas, such as social security reform.\(^3\) This is surprising because social security is one of the most important public policy areas. Major reforms have been implemented world-wide over the past couple of decades and more is to come. The primary goal of these reforms is to restore fiscal sustainability and make people work longer. Existing evidence show that social security is, in fact, a key determinant of late-in-life labor supply.\(^4\) Social security reforms are often announced years in advance. For example, In Denmark a major reform of the social security eligibility rules was announced in 2006 to take effect for people becoming eligible in 2019. Similarly, the US Social Security Amendments of 1983 raised the age of eligibility for unreduced retirement benefits to 67 by the year 2027.\(^5\) One goal of such early announcements is provide ‘forward guidance’ to workers of all ages to allow them to plan their labor force participation as well as spending and savings strategies more effectively. Yet, communication efforts are essentially passive. In both the US and in Denmark, information is made available on official websites and a personalized social security statement can also be accessed by the citizens in both countries\(^6\), but people

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\(^1\) 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](https://www.ecb.europa.eu/home/search/review/html/monpol-communication.en.html)

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

\(^3\) This extends to other domains where complexity is often high. This includes tax policies and where people are left confused, e.g., Chetty and Saez (2013) and Kostol and Myhre (2021) and benefit program take-up, e.g., Currie (2006), Finkelstein and Notowidigdo (2019), Kleven and Kopczuk (2011).


\(^5\) [https://www.ssa.gov/history/1983amend.html](https://www.ssa.gov/history/1983amend.html)

\(^6\) In the US it can be accessed at the Social Security Administration and in Denmark it can be accessed at [www.pensioninfo.dk](http://www.pensioninfo.dk)
actively need to search for this information.

Recent research raises concerns about how many workers actively pursue up to date information about social security rules. For example, 40% of American workers are unaware of when they will become eligible for social security benefits. Many also view social security entitlements as uncertain (Luttmer and Samwick, 2018). The open question is the extent to which more active and deliberate communication might dispel confusion about eligibility. The challenge is that it is hard to separately identify fundamental policy uncertainty associated with changing demographic and political factors from uncertainty that results from inattention to currently available information because uncertainty might itself be a reason for inattention. This distinction between largely unavoidable uncertainty about the future and inattention to currently available information is fundamental to the role of communication. If uncertainty is largely about fundamental future uncertainties, communicating current policies better will have little effect (Kosar and O’Dea, 2021, Ciani et al., 2019). If instead it is largely a result of passive learning by workers, then more active and better targeted communication has potentially large effects.

One promising path forward involves building on the recent literature of information treatments (Haaland et al., 2022) to tease apart fundamental uncertainty about the future from inattention to currently available information. In an ideal case one would implement an information treatment that overcomes informational frictions altogether, leaving only the fundamental uncertainty in place. In this paper we implement an information treatment that is close to ideal in this regard. Denmark in 2006 replaced a long-standard policy with universal social security eligibility at age 65 with longevity-based eligibility. This reform changed only eligibility age, without changing other features of the social security benefit system. This allows us to implement a strikingly simple information treatment: before posing questions about future 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. All this does is to overcome passive learning. For both groups we measure probabilistic beliefs using the balls and bins protocol of Delavande and Rohwedder (2008) such that we can characterize the entire subjective probability distribution concerning social security eligibility and how active communication influences it.

As simple as is the treatment, so are the results. Absent treatment, beliefs about eligibility reveal high uncertainty but also systematic bias. Younger workers’ beliefs about social security

\footnote{see e.g. 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).}

eligibility are significantly biased, expecting to become eligible for social security significantly younger than is planned according to current policy, as if anchored in the past.\footnote{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 literature 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 for a review of the literature on experienced based belief formation.)} In line with rational inattention, beliefs about eligibility is most biased for those for whom social security payments form a smaller proportion of expected income in retirement and for those who have many years to reaching eligibility, i.e., the young. The information treatment essentially eliminates the gap between the statutory eligibility age and subjective mean beliefs, and it affects beliefs about retirement too. The effect of the information treatment on uncertainty is entirely different. We find that the treatment does not influence subjective uncertainty suggesting that it is largely driven by unavoidable demographic and political uncertainties. This is not surprising since changes can and have been made since the initial announcement, and because the Danish policy explicitly introduces fundamental demographic uncertainty since future eligibility ages depend on future life expectancy. We develop a model to capture how beliefs about social security eligibility are jointly shaped by information and policy uncertainty. A calibrated version of the model matches the findings from the survey data.

An critical and open question concerns how long the information treatment is retained, particularly if there is no immediate decision involved which is the case with social security. As Sims (2010) note, simple and salient communication is more likely to catch people’s attention and make them remember. A follow-up survey one year later shows that the effect of the information treatment in the original survey dissipates only slowly indicating that it is in fact possible to influence people’s beliefs durably and break the grip of the past. Our results highlight the need to treat active communication as an integral part of policy design. Passively making information available produces misunderstanding that would be avoided by a more deliberate communication policy. Measurement of beliefs is key as this is the most direct way to learn whether the public internalizes policy communication. Altogether this suggests that there may be many benefits of extending use of belief measurement and information treatments (as reviewed by Haaland et al. (2022)) into many areas of policy beyond the monetary policy context.

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 life expectancy 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.

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.\textsuperscript{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 the development 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 is 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.\textsuperscript{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 published as early as 2006 (DREAM, 2006) and today it is straightforward 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 1971 or younger, social security eligibility is assumed to be 69. Different

\textsuperscript{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.

\textsuperscript{11}The benefit structure was not affected by the reform. We describe the social security benefit structure in Appendix A.
Table 1: Social Security Eligibility Age by Year and Birth Cohort

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

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.

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 is 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 sex of the individual. For conducting our survey, we have 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, i.e., the sample of 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. 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 records 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 until and including 2020. In Table 3 in 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 Appendix C, Figure 6, we present a screen shot of the balls-in-bins screen.

For each respondent, \( i \), we then estimate the mean, \( \mu_i \), and standard deviation, \( \sigma_i \), of the subjective probability distribution:

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

where we assume that each ball, \( x_{ib} \), takes the value of the midpoint of the bin.\(^{12}\)

\(^{12}\)Each bin is two years wide, the midpoint of each bin are the odd numbers - for example, for the bin “68-69”, the midpoint is 69. If a respondent believes she has a statutory 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 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.
The interval presented to the respondents turned out to be too narrow. Some of the younger respondents, in particular, allocated many balls into the 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 Appendix C we describe the 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. Also for these questions beliefs are elicited using the balls-in-bins method. The questions are described in detail in Appendix D. In the administrative data we observe third-party reported counterparts to the respondents’ income and pension wealth. In 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

The information treatment is very simple. 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:

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]

13In 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 Appendix C.1, and they are for all practical purposes identical to the results based on the triangular distribution.
The information treatment experiment was conducted in both the baseline survey and in the follow-up survey. In the follow-up survey, participants were randomized again.

4 Results

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.

Figure 1a shows statutory social security eligibility ages with horizontal lines. The solid line shows average subjective means of beliefs about social security eligibility age by birth cohorts for the control 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 eligibility age beliefs are increasing in distance to eligibility and that 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 mean of stated beliefs, widens such that the eligibility age beliefs are consistently smaller than the eligibility ages listed in Table 1.

The pattern for the baseline group shown in Figure 1a is interesting. It 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.

The dotted line in Figure 1a shows the average of the subjective mean of beliefs, \( \mu_i \), for the group that was information treated. It is evident that the average of mean beliefs of the treated group is closer to the statutory eligibility ages, indicating that the information treatment reduces the eligibility gap. The average of subjective mean beliefs tracks the statutory eligibility ages closely up until around cohort 1970. For younger cohorts the eligibility gap widens.\(^{14}\) 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 averages of subjective variances by birth cohort organized in the same way as Figure 1a. The solid line in Figure 1b shows that the average subjective uncertainty (measured as the individual variance, \( \sigma_i^2 \)) pertaining to the belief about the social security eligibility age,

\(^{14}\)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 13 in 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.
**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 statutory 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.

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 pertaining to the belief about the social security eligibility age for the group that was information treated. The pattern for the average of subjective variances almost coincide with that of the control group, i.e., subjective uncertainty is not affected by the treatment.

5 A Model of Policy Beliefs

In this section 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 4.

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 15Such 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/
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 \( q = 2 \) and assume that the eligibility age under either policy is characterized by a normal distribution capturing the underlying uncertainty: \( f_{q,k} \sim \mathcal{N}(\mu_{q,k}, \sigma_{q,k}^2) \) where \( q = 1,2 \), and \( k \) is an indicator for the cohort group, c.f., Table 1. The subjective beliefs about eligibility age, \( f \), is given by the mixture of the two normal distributions

\[
\begin{align*}
    f_{1,k} &\sim \mathcal{N}(\mu_{1,k}, \sigma_{1,k}^2) \\
    f_{2,k} &\sim \mathcal{N}(\mu_{2,k}, \sigma_{2,k}^2) \\
    f_{k,D} &= p_{k,D} f_{1,k} + (1 - p_{k,D}) f_{2,k}
\end{align*}
\]  

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 \( k \) 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:

\[
\begin{align*}
    m_{k,D} &= E[f] = p_{k,D} \mu_{1,k} + (1 - p_{k,D}) \mu_{2,k} \\
    s^2_{k,D} &= \text{Var}[f] = p_{k,D} \sigma_{1,k}^2 + (1 - p_{k,D}) \sigma_{2,k}^2 + p_{k,D} (1 - p_{k,D}) (\mu_{1,k} - \mu_{2,k})^2
\end{align*}
\]  

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 \( p_{k,D} \).

\[\text{kommissioner-ekspertudvalg/kommissionen-om-tilbagetraekning-og-nedslidning}\]

\[\text{16We use cohort groups that correspond to the eligibility ages, c.f., Table 1. The data used to fit the model is cohort group specific average moments.}\]
5.1 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 in Table 1. 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 \( \mu_2,k \in \left[ \min(m_{k,C}), \mu_1,k \right] \) where \( \min(m_{k,C}) \) 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).

In Figure 2 we report the model’s ability to replicate average mean beliefs, Panel 2a, and uncertainty, Panel 2b, by information treatment status. Panel 2a 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 2b 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.

In the model described by Equations (4) and (5) the effect of the information treatment

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\[ ^{17} \text{We refer to Appendix G for details about the minimum distance procedure.} \]
Notes: Panels 2a and 2b show the results from fitting Equations (4) and (5) to average subjective means, Panel 2a, and variances, Panel 2b, separately for all cohort groups and for treated and untreated individuals. Solid lines are data moments and dashed lines are fitted values. In Panel 2a, ‘+’s indicate $\mu_{1,k}$, which is fixed to match statutory eligibility ages listed in Table 1, and ‘×’s are fitted values of $\mu_{2,k}$. In Panel 2b, ‘+’s are fitted values of $\sigma^2_{1,k}$ and ‘×’s are fitted values of $\sigma^2_{2,k}$.

operates through shifting the subjective weight on the life table policy, $p_{k,D}$. In Figure 3 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.

6 Extensions

6.1 Retirement beliefs

Social security eligibility is not a choice variable, but rather a circumstance that people are facing. Retiring from the labor market is, however, a choice and previous studies have shown evidence that retirement is excess 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. In particular, Amin-Smith and Crawford (2018) and MacCuish (2022)
show that mistaken beliefs about the eligibility age are predictive of the employment response upon reaching eligibility, indicating that mistaken beliefs are important for understanding the employment sensitivity to the statutory eligibility age.

In the baseline survey we elicit beliefs about when the respondents expect to retire. We do this using the balls-in-bins methodology that we also used for eliciting social security eligibility. The specific question is listed in the Appendix D. In Figure 4 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 also affects retirement plans. Panel 4a shows that mean retirement age beliefs are close to the social security age for the oldest cohorts who are close to their statutory social security eligibility age, but that younger cohorts consistently expect to retire before they become eligible for social security. Panel 4b shows that the subjective variance of retirement age beliefs increase 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 the variance is left practically unaffected across cohorts. This pattern broadly tracks the patterns documented for the social security eligibility beliefs suggesting that social security beliefs do impact retirement plans.

We also find evidence that the degree to which retirement beliefs are sensitive to the beliefs about the social security eligibility age increases with the importance of social security payments.

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 2 shows the fit of the four moments of the common underlying distributions, \( f_{q,k} \).
in overall expected income during retirement. This shows that incentives matter. We find that individuals with above-median retirement sensitivity tend to be better informed than people who have below-median retirement sensitivity. Still, people have downwards biased eligibility beliefs irrespective of their incentive, and these beliefs are corrected to almost completely align with the statutory eligibility ages when information treated. These results, which are reported in Appendix H, 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.

6.2 Follow-up survey

In 2022, one year after the original survey, we conducted a follow-up survey where we repeated the information treatment experiment. In Figure 5 we show four panels where 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 5a 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 statutory ages. From 2021 to 2022, the beliefs are shifted slightly up. This may reflect that participation in the 2021 survey induced people to acquire more information about social security information. Figure 5b 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 5b looks similar to Figure 1a suggesting that our experimental results are not driven by selection into the survey. Figure 5c shows beliefs for 2021 and 2022 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 statutory eligibility ages. This confirms the effectiveness of the information treatment in updating people’s eligibility beliefs. Finally, in Figure 5d 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 slightly towards a lower social security eligibility age in 2022. This suggest that respondents clearly remember the treatment after one year, but it also suggests that memory decay likely plays a role.\textsuperscript{18}

**Figure 5:** Follow-Up Survey by Treatment Status in 2021/2022, Mean

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 statutory eligibility ages. See notes to Figure 1 for details.

\textsuperscript{18}The corresponding figures for the subjective variances are shown in Appendix I.
7 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 implemented across the world, but people tend to be confused about the rules. This may be because demographic and political uncertainties can cause social security rules to be amended in the future, or because people are simply uninformed. It is an open question whether improved communication could significantly lower confusion about social security.

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 and implement a strikingly simple information treatment experiment where we communicate the longevity-based plan as currently available on the official Website to half the sample. We find that beliefs for the untreated group are biased towards the old policy. Treatment aligns social security eligibility beliefs with current rules, but they do not affect perceived uncertainty.

Our results points towards poor communication as a primary source of confusion when it comes to social security policy. Moreover, it highlights the widespread need to integrate communication strategies, including belief measurement and information treatments, into policy design more generally.
References


### 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>
<thead>
<tr>
<th>Table 2: Yearly Social Security Benefits (DKK), 2021</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic</strong></td>
</tr>
<tr>
<td><strong>Supplement</strong></td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
</tbody>
</table>

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, 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 3: Balance Table

<table>
<thead>
<tr>
<th></th>
<th>Baseline survey 2021</th>
<th></th>
<th>Follow-up survey 2022</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Participants</td>
<td>Non-participants</td>
<td>Difference</td>
<td>Participants</td>
</tr>
<tr>
<td>N</td>
<td>9572</td>
<td>62594</td>
<td></td>
<td>3540</td>
</tr>
<tr>
<td>female</td>
<td>0.492</td>
<td>0.493</td>
<td>-0.001</td>
<td>0.476</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>(0.006)</td>
<td>(0.499)</td>
</tr>
<tr>
<td>age</td>
<td>48.389</td>
<td>43.601</td>
<td>4.788</td>
<td>52.68</td>
</tr>
<tr>
<td></td>
<td>(12.179)</td>
<td>(12.8)</td>
<td>(0.135)</td>
<td>(11.218)</td>
</tr>
<tr>
<td>college</td>
<td>0.488</td>
<td>0.341</td>
<td>0.148</td>
<td>0.501</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.474)</td>
<td>(0.005)</td>
<td>(0.5)</td>
</tr>
<tr>
<td>employed</td>
<td>0.842</td>
<td>0.785</td>
<td>0.057</td>
<td>0.839</td>
</tr>
<tr>
<td></td>
<td>(0.365)</td>
<td>(0.411)</td>
<td>(0.004)</td>
<td>(0.367)</td>
</tr>
<tr>
<td>earnings</td>
<td>408,197</td>
<td>325,309</td>
<td>82,888</td>
<td>428,503</td>
</tr>
<tr>
<td></td>
<td>(311,201)</td>
<td>(311,782)</td>
<td>(3,431)</td>
<td>(335,858)</td>
</tr>
<tr>
<td>wealth</td>
<td>443,926</td>
<td>248,848</td>
<td>195,078</td>
<td>519,329</td>
</tr>
<tr>
<td></td>
<td>(4,792,147)</td>
<td>(2,620,078)</td>
<td>(50,299)</td>
<td>(1,673,064)</td>
</tr>
<tr>
<td>pension</td>
<td>1,579,293</td>
<td>993,810</td>
<td>585,483</td>
<td>1,894,543</td>
</tr>
<tr>
<td></td>
<td>(1,874,468)</td>
<td>(1,490,113)</td>
<td>(20,150)</td>
<td>(1,944,205)</td>
</tr>
</tbody>
</table>

#### Table 4: Tabulation of observations by social security eligibility age

<table>
<thead>
<tr>
<th>Eligibility age</th>
<th>Baseline survey 2021</th>
<th>Follow-up survey 2022</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control</td>
<td>Treatment</td>
</tr>
<tr>
<td>67.00</td>
<td>1,248</td>
<td>1,297</td>
</tr>
<tr>
<td>68.00</td>
<td>614</td>
<td>591</td>
</tr>
<tr>
<td>69.00</td>
<td>586</td>
<td>520</td>
</tr>
<tr>
<td>70.00</td>
<td>496</td>
<td>488</td>
</tr>
<tr>
<td>71.00</td>
<td>384</td>
<td>421</td>
</tr>
<tr>
<td>72.00</td>
<td>331</td>
<td>344</td>
</tr>
<tr>
<td>73.00</td>
<td>293</td>
<td>322</td>
</tr>
<tr>
<td>73.50</td>
<td>306</td>
<td>318</td>
</tr>
<tr>
<td>74.00</td>
<td>289</td>
<td>263</td>
</tr>
<tr>
<td>74.50</td>
<td>227</td>
<td>234</td>
</tr>
</tbody>
</table>
C The Balls-in-Bins Survey Instrument

Figure 6 shows 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 6: Balls-in-Bins](image)

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 6.

The procedure is illustrated with an example in Figure 7. 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 \( \gamma \) (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

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

\(^{19}\)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 7 shows how the imposed
distribution looks.

**Figure 7**: *Balls in bins, imposing a triangular distribution*

![Figure 7](image)

*Notes*: The balls-in-bins instrument has a cap at “74 or older”. For distributions where “74 or older” has any
balls, 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 5 the fraction
of responses that we have corrected is listed.

**Table 5**: *Fraction of observations within each cohort group on which symmetry is imposed*

<table>
<thead>
<tr>
<th>Eligibility age</th>
<th>Fraction with imposed triangular distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>67.00</td>
<td>0.02</td>
</tr>
<tr>
<td>68.00</td>
<td>0.04</td>
</tr>
<tr>
<td>69.00</td>
<td>0.08</td>
</tr>
<tr>
<td>70.00</td>
<td>0.17</td>
</tr>
<tr>
<td>71.00</td>
<td>0.28</td>
</tr>
<tr>
<td>72.00</td>
<td>0.38</td>
</tr>
<tr>
<td>73.00</td>
<td>0.44</td>
</tr>
<tr>
<td>73.50</td>
<td>0.51</td>
</tr>
<tr>
<td>74.00</td>
<td>0.52</td>
</tr>
<tr>
<td>74.50</td>
<td>0.53</td>
</tr>
</tbody>
</table>

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 8 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 8: 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 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 Greene (2003) we use the fraction of balls, \( \gamma \), located in bins lower than the cut-off, \( a = 74 \) (all except "74 or older"), and calculate the quantile function of \( \gamma \) (the inverse of the cumulative distribution function for a Gaussian distribution):

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

We then calculate the auxiliary variable, \( \lambda \), (where \( \phi \) is the Gaussian probability density function):

\[
\lambda = \frac{\phi(\alpha)}{\gamma}
\]

The mean of the truncated distribution is given by (Greene (2003)):

\[
E[x|x < a] = \mu + \lambda \sigma
\]

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}

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

Solving these yield the parameters of the underlying distribution, \( \mu \) and \( \sigma \). Figure 9 shows the results. The results are practically identical to the case where we use the triangular distribution. Figure 10 and 11 show results for 2021 and 2022 beliefs in the follow-up sample based on the assumption that the underlying distribution is Gaussian. Again, the results are for all practical purposes similar.
Figure 9: 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 9a, and subjective variance of eligibility ages, Panel 9b. Censored distributions are imputed assuming a Gaussian distribution. See notes to Figure 1. In Panel 9a horizontal lines show statutory eligibility ages.

Figure 10: Follow-Up Survey by Treatment Status in 2021/2022, Mean. Imputed Gaussian distribution for censored 2021 answers

(a) No-No

(b) No-Yes

(c) Yes-Yes

(d) Yes-No

Notes: Lines show locally weighted linear regressions for subjective mean eligibility ages for control (solid) and treatment (dotted) group for each combination of control and treatment in the baseline and the follow-up survey. Censored distributions are imputed assuming a Gaussian distribution. See notes to Figure 1. Horizontal lines show statutory eligibility ages.
Figure 11: Follow-Up Survey by Treatment Status in 2021/2022, Variance. Imputed Gaussian distribution for censored 2021 answers

Notes: Lines show locally weighted linear regressions for subjective variance of eligibility ages for control (solid) and treatment (dotted) group for each combination of control and treatment in the baseline and the follow-up survey. Censored distributions are imputed assuming a Gaussian distribution. See notes to Figure 1.
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. Panel 12a 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 12b 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 12 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 12: Validation of Survey Responses**

![Figure 12](image)

(a) Mean reported pension savings, 2020  
(b) Mean reported earnings, 2020

*Notes: The figure shows the relationship between reported pension wealth, Panel 12a, (earnings, Panel 12b) 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 13: *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 Minimum Distance

In Section 5 we fit our model of belief updating. The model is specified by equations (4) and (5).

The model has six parameters for each cohort, \( p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma_{1,k}^2, \mu_{2,k}, \sigma_{2,k}^2 \). We observe average subjective means and variances, i.e., \( \bar{m}_{k,C}, \bar{m}_{k,T}, \bar{s}_{k,C}^2, \) and \( \bar{s}_{k,T}^2 \) 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 1. Next, we assume that \( \sigma_{2,k}^2 \geq \sigma_{2,k-1}^2 \) and \( \sigma_{1,k}^2 \geq \sigma_{1,k-1}^2 \). Finally, we restrict \( \mu_{1,k} \in \left[ \min(m_{k,C}), \mu_{2,k} \right] \) where \( \min(m_{k,C}) \) 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, \( p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma_{1,k}^2, \sigma_{2,k}^2 \) by minimizing the squared distance between the empirical moments, \( \bar{m}_{k,C}, \bar{m}_{k,T}, \bar{s}_{k,C}^2, \) and \( \bar{s}_{k,T}^2, \) 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):

\[
\Theta = \arg\min_{p_{k,C}, p_{k,T}, \mu_{1,k}, \sigma_{1,k}^2, \sigma_{2,k}^2} \left[ (m_{k,C} - \bar{m}_{k,C})^2 + (m_{k,T} - \bar{m}_{k,T})^2 + (s_{k,C}^2 - \bar{s}_{k,C}^2)^2 + (s_{k,T}^2 - \bar{s}_{k,T}^2)^2 \right]
\]

subject to

\[
\begin{align*}
\sigma_{1,k}^2 & \geq \sigma_{1,k-1}^2 \\
\sigma_{2,k}^2 & \geq \sigma_{2,k-1}^2 \\
\mu_{1,k} & \in \left[ \min(m_{k,C}), \mu_{2,k} \right]
\end{align*}
\]
H The Importance of Incentives for Retirement Beliefs

The importance of social security payments for people 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 also be more attentive to changes in social security eligibility and this is potentially an important source of heterogeneity.

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 how retirement sensitivity predicts the effect of the information treatment.

To quantify how sensitive 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 policy, as well as retirement beliefs conditional on being eligible as specified in Table 1. We refer to Appendix D for the exact wording of the questions.

Retirement sensitivity \( RS \) is defined

\[
RS = \frac{E[\text{RetAge}|\text{TableAge}] - E[\text{RetAge}|\text{Age65}]}{\text{TableAge} - 65}
\] (7)

\( RS \) essentially quantifies how much the mean expected retirement age is moved relative to how much the social security eligibility policy changes the social security age. We also elicit beliefs about expected retirement income arising from pension savings (see Appendix D).

To learn about how retirement sensitivity varies with the importance of social security in retirement income, we present in Figure 14 a plot of retirement sensitivity, \( RS \), 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 clearly negatively correlated with the expected retirement income level. This indicates that the financial incentive matters for the retirement sensitivity to the social security eligibility age.

In order to investigate how retirement sensitivity impact the beliefs about social security eligibility, we split the sample in to two equally sized groups by the size of the retirement sensitivity measure, \( RS \). The results are shown in Figure 15. The low sensitivity group has a
Figure 14: Pension income, deciles

Notes: The figure shows a locally weighted linear regression for the relationship between retirement sensitivity (c.f., equation (7)) and deciles of expected pension income. See notes to Figure 1.

large eligibility gap, and the high sensitivity group has a small eligibility gap. The treatment reduces the eligibility gap for both groups.

Figure 15: Social Security Eligibility Beliefs by above/below Median Retirement Sensitivity

Notes: Lines show locally weighted linear regressions for control (solid) and treatment (dotted) groups for subjective mean eligibility ages, Panel 15a, and subjective variance of eligibility ages, Panel 15b. Light error bands indicate above median retirement sensitivity, dark error bands indicate below median retirement sensitivity. See notes to Figure 1. In Panel 15a horizontal lines show statutory eligibility ages.
I Further Evidence from the Follow-Up Survey

In Figure 16 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 5. The samples underlying the panels in Figure 16 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 1b. Generally there appears to be no effect of the information treatment, albeit in Figure 16d, 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 16: 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 1 for details.