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Labor Supply vs. Demand of OlderWorkers

A Structural Approach with Stated Preferences

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Labor Supply vs. Demand of Older Workers: A Structural Approach with Stated Preferences

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Abstract

Many workers retire abruptly from full-time employment, a pattern that standard life-cycle models with smooth preferences over leisure and consumption struggle to reconcile. This suggests that factors other than those governing preferences for labor supply – such as institutional and demand-side forces, including firms' limited willingness to offer part-time work to older employees – play an important role. Distinguishing between these supply- and demand-side factors is challenging, as both shape observed labor supply behavior. We address this challenge by developing a new identification strategy that combines observational data with stated preferences for part-time work from strategic survey questions. Our preliminary results reveal that prime-aged men do not want to work part-time, exhibiting negative willingness to pay to reduce hours worked. However, their willingness to pay for part-time work becomes positive and sizable close to retirement age. In contrast, female reservation wages are sharply rising in hours worked, indicating that women do not want to work full-time. Viewed through the lens of our structural life-cycle model, these patterns are consistent with a large labor supply elasticity for women, and a slightly smaller elasticity for men.

JEL Classification: D15, H31, H55, J22, J23

Keywords: Retirement, Labor Supply, IES

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1 Introduction

A striking feature of retirement behavior in many countries is the abrupt transition from full-time work directly into retirement. In the Netherlands, for example, nearly half of all workers retire directly from full-time jobs without passing through intermediate arrangements. This is true despite institutional flexibility in the Netherlands that allows individuals to combine part-time work and part-time pensions, and moreover allows workers to choose their part-time hours. It is hard to reconcile abrupt retirement with the standard life-cycle model. Standard theory predicts that individuals smooth out leisure (and consumption) over age. While movement in relative prices or preferences can generate a gradual decline in hours worked with age, it is difficult to rationalize an abrupt decline. In particular, life-cycle models with smooth preferences over leisure and consumption predict more gradual transitions, unless individuals display implausibly high intertemporal elasticities of substitution for labor supply or very steep increases in the marginal value of leisure around the retirement age. This puzzle suggests that factors beyond standard supply-side preferences play an important role in shaping older individuals' labor market outcomes.

When directly asked in surveys, older workers state strong preferences for flexible work arrangements and alternative workplace characteristics. In 2019, almost half of workers in the Netherlands would be willing to remain employed longer if the possibility of working fewer hours or less days per week were available, according to the Nationale Enquete Arbeidsomstandigheden. Another 25% reported that they would continue working longer, if the pressure associated with their job was lower. Yet, little is known about how much workers would be willing to sacrifice in terms of salary for such work arrangements.

We build on Rogerson and Wallenius (2013), who show that abrupt retirement can arise not only from labor supply factors but also from demand-side frictions, such as firms' limited willingness to provide flexible or part-time work opportunities for older employees. In particular, if part-time work is valued less than full-time work by firms, hourly wages may increase with hours worked, effectively creating a part-time wage penalty. Distinguishing between these supply- and demand-side channels is, however, empirically challenging, as both shape observed labor supply behavior.

Our contribution is to develop a new identification strategy that combines observational data with stated-preference data from strategic survey questions (SSQs). Following Ameriks et al. (2020), we designed and fielded a new SSQ module in the Dutch Longitudinal Internet Studies for the Social Sciences (LISS) Panel, a probability-based survey of 5,000 households. Respondents first describe a 'reference job' (either their current job or their longest past job), which anchors realistic job characteristics such as earnings, hours, physical demands, stress, and flexibility. They are then presented with a series of hypothetical job choices in which one characteristic is altered at a time, alongside an outside option of not working. For each choice, we elicit reservation wages, which allow us to compute willingness to pay (WTP) for alternative job characteristics, such as part-time hours or greater flexibility.

We use these stated preferences to separately identify supply-side parameters of a structural life-cycle model, including the intertemporal elasticity of substitution for labor supply and the marginal utility of leisure, independently of demand-side conditions. Once the supply-side is pinned down, demand-side factors – particularly the part-time wage penalty – can be inferred by comparing simulated behavior under the model with actual labor supply outcomes observed in the data. In the model, individuals aged 50 and older make decisions about consumption and savings, whether to work or to retire, whether or not to claim occupational pension, and if working how many hours to work (choice between four discrete hours choices). The hourly wage is increasing in hours worked, so part-time work is associated with a wage penalty. Occupational pension claiming and retirement are assumed to be absorbing states.

We use the survey data to predict reservation wages by gender, age, and hours worked, controlling for assets, pension points, relationship status and education. We also compute the WTP to reduce weekly hours worked by 10 hours by gender, age and hours worked for an individual with average assets and pension points. We document sizable gender differences in the patterns for reservation wages and WTP to reduce hours worked. On average, prime-aged men do not want to work part-time. The predicted reservation wage schedule for men at age 55 is decreasing in hours worked. Moreover, the willingness of these individuals to pay to reduce hours worked is negative at all weekly hours between 25 and 45. Intuitively, as men get older, they are more inclined to want to reduce hours worked. The predicted reservation wage schedule for 65 year old males is increasing in hours worked (or slightly U-shaped). This translates into a positive WTP to reduce hours worked. In fact, the average man would be willing to forgo roughly 3% of his hourly wage to reduce weekly hours worked from 40 to 30. Conditional on hours worked, reservation wages are increasing in age. In contrast, women typically do not want to work full-time. The predicted reservation schedules are steeply increasing in hours worked at all ages (consider women aged 50 and older). Moreover, the reservation wages for women are also increasing in age.

The differences in predicted reservation wages over gender, age and hours worked pin down the supply side parameters, namely the intertemporal elasticity of substitution and the disutility of labor supply. The disutility parameters govern the general willingness to work and thus the reservation wage level. The elasticity in turn is pinned down by how reservation wages vary with hours of work. We show that a large elasticity is consistent with the predicted reservation wage schedules for females, while a somewhat smaller elasticity can rationalize the reservation wage patterns for males.

Having pinned down the supply side parameters, the next step is to use our fully-fledged quantitative model to pin down the demand side parameters, namely the part-time wage penalty. From the survey we can already conclude that the coexistence of full-time workers with positive WTP for part-time work and part-time workers with positive WTP for full-time work suggests the presence of a non-trivial part-time wage penalty. Together, these results indicate that demand-side frictions likely play an important role in shaping retirement behavior. Our two-step estimation procedure – first identifying supply-side parameters from SSQs, and then estimating the demand-side part-time wage penalty from behavioral moments – will allow us to quantify the relative importance of supply, demand, and institutional factors in driving abrupt retirement. There is much scope for interesting future work, as our rich life-cycle model can ultimately be used for policy and welfare analysis. In particular, we ultimately aim to evaluate the welfare gains of removing demand-side frictions at firms and the welfare effects of pension reforms that alter retirement incentives.

Related Literature. There is a large literature using variation in hours and wages over the life cycle to estimate the intertemporal elasticity of substitution of labor supply dating back to MaCurdy (1981). See, e.g., Pencavel (1986) for a survey of the older literature and Chetty (2012) for a more recent synthesis of the literature. Much of this literature on estimating the intertemporal elasticity of substitution of labor supply focuses on prime-aged individuals. Rogerson and Wallenius (2013) argue that the abrupt transition from full-time work to essentially no work is also informative about the magnitude of the labor supply elasticity. Intuitively, since this elasticity speaks to individuals' desire to smooth leisure over the life cycle, their willingness to incur a dramatic change in leisure time at retirement sheds light on their willingness to intertemporally substitute. Rogerson and Wallenius (2013) derive an expression that links hours worked prior to retirement, the intertemporal elasticity of substitution for labor supply, and the size of non-convexities, namely the degree to which the wage is increasing in hours worked. They show that to generate realistic retirement behavior, either the non-convexity or the labor supply elasticity must be very large. However, their setting does not allow them to separately pin down the two parameters.

Uncovering the WTP for job amenities is crucial in disentangling the demand and supply side factors in shaping retirement behavior. Ameriks et al. (2020) investigate the role of flexibility in governing retirement decisions. By eliciting reservation wages for both flexible and fixed working conditions, their approach isolates the interplay between labor supply elasticities and market constraints. Their model links observed retirement behavior to unobserved preferences for job characteristics and uses these insights to estimate the intertemporal elasticity of substitution of labor supply. They find that older workers exhibit a strong preference for flexible working conditions, even at the cost of significant wage reductions. Our work builds on the approach of Ameriks et al. (2020). We too use stated preferences to help pin down the intertemporal elasticity of substitution of labor supply, but we propose a novel identification strategy. We extend the set of considered job amenities by not only eliciting the desire to reduce hours, but also the preference for other flexibilities (such as home office possibilities), less stress, or less physical demands. Moreover, we set up a fully fledged, quantitative, dynamic life-cycle model that will ultimately allow us to quantify the effects of a more flexible labor market on retirement decisions and crucially on welfare. Lastly, our survey is representative of the entire population aged 50 and above, and not only for a subgroup of wealthy individuals.

There are a number of studies using surveys to elicit preferences for job amenities. Eriksson and Kristensen (2014) pioneered the use of vignettes to elicit preferences for fringe benefits, including health insurance, flexible scheduling, and other perks. Building on this, Mas and Pallais (2017) introduced stated preference methods to estimate WTP for flexible scheduling and remote work in a large sample of call center employees. These studies revealed significant demand for job flexibility and better work-life balance. Recent studies have expanded the focus to older workers, whose preferences often differ from those of younger individuals. Hudomiet et al. (2021) examine how job characteristics, such as reduced stress, physical effort, and flexible scheduling influence older workers' likelihood of remaining employed at age 70. They find that preferences for flexibility, reduced job stress, and shorter commutes dominate for older individuals. Similarly, Maestas et al. (2023) use discrete choice experiments to assess older workers' WTP for a broad range of job attributes, including autonomy, physical activity, and schedule flexibility. Their findings underscore the importance of these attributes, with older workers exhibiting a substantial WTP for greater autonomy and moderate physical activity in their jobs. Additionally, Nagler et al. (2023) and Nagler et al. (2024) study the WTP to avoid job stress and commuting, respectively, using data from Germany. This literature helped guide our survey design and caused us to zoom in on four main job characteristics that are crucial for older workers, namely the freedom to: (1) adjust working hours, (2) increase scheduling and workplace flexibility, (3) adjust the stress level at work, and (4) reduce physical demands at the workplace. These amenities are the focus of our survey.

Our paper also connects to the literature on the part-time wage penalty. There is some empirical work estimating the effect of non-convexities in wages, see Moffitt (1984) and Aaronson and French (2004). Bick et al. (2022) document significant wage penalties in the US for people who deviate in either direction from 40 hours per week, leading to a large mass of individuals who work 40 hours per week.

The remainder of the paper is structured as follows. Section 2 presents some motivating, stylized facts from the observational data. Section 3 describes the survey, while Section 4 presents the empirical results from said survey. Section 5 present a simple toy model to illustrate our novel identification strategy. Section 6 presents the full quantitative model. Section 7 details the estimation. Section 8 concludes.

2 Liss Panel and Stylized Facts

In this section, we document a few stylized facts about the labor supply behavior of older men and women in the Netherlands.

2.1 Data

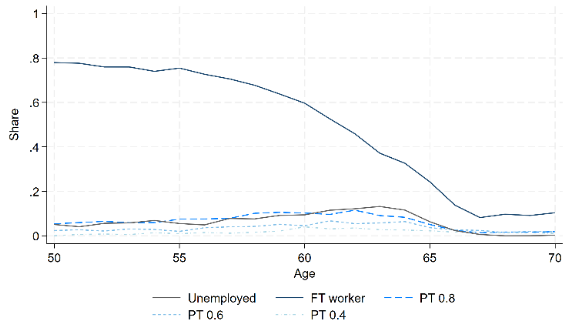
This analysis utilizes two data sources. First, we use the Longitudinal Internet Studies for the Social Sciences (LISS) panel, which is an ongoing online survey of around 5,000 households, comprising approximately 7,500 individuals aged 16 and older. It was launched in 2007.[1] The panel is based on a true probability sample of households drawn from the population register of Statistics Netherlands and includes only respondents who were invited to participate. Second, we collect our own data based on an add-on survey to the LISS panel. The details on the survey are described in Section 3.

2.2 Stylized Facts on Labor Supply

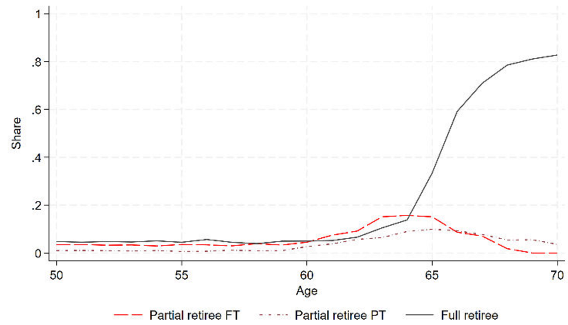
We start by documenting some stylized facts around the labor supply behavior of older individuals in the Netherlands. Panel (a) of Figure 1 shows the prevalence of full-time and part-time work among men aged 50 to 70. Panel (c) documents the same for women. Full-time work is defined as 36 hours or more per week. Dutch workers have considerable flexibility in choosing part-time hours. Thus, the figure shows the prevalence of part-time work that corresponds to 80%, 60%, and 40% of full-time hours. The prevalence of full-time vs. part-time work varies considerably over gender, with the share of men engaged in full-time work considerably higher than the share of women. The share of men working full-time at age 50 is close to 80%. This drops to roughly 60% at age 60, and further to just below 25% at age 65. A sizable fraction of men in the Netherlands work part-time, particularly shortly before retirement, with slightly less than 20% men working part-time at age 60. Most men who work part-time, work 80% of full-time hours. Part-time work among women is very prevalent in the Netherlands. In fact, only approximately 20% of women work full-time at age 50, while 70%

[1] See https://www.dataarchive.lissdata.nl/study-units/view/1 for codebooks.

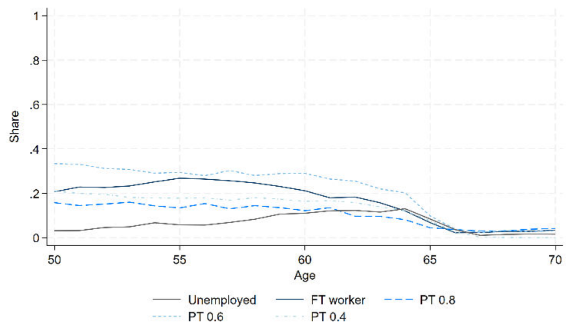
work part-time. The part-time hours of women vary considerably, but working 60% of full-time hours is the most prevalent arrangement. Despite the large differences in the prevalence of full-time and part-time work, the employment rates over age look remarkably similar for men and women. Thus, the timing of retirement is roughly the same for both genders. In the Netherlands, it is possible to combine part-time work with partial pension. Panels (b) and (d) report the prevalence of partial and full pension over age for men and women, respectively.



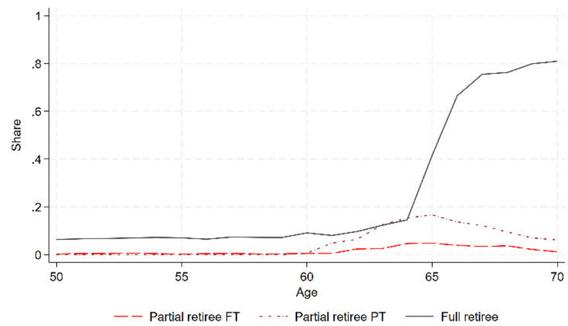
(a) Males: workers and unemployed



(b) Males: retirees



(c) Females: workers and unemployed



(d) Females: retirees

Figure 1: Employment status by age and gender

Next, we zoom in on the transition from work to retirement. Figure 2 shows that, between 2012 and 2023, slightly less than half of retiring individuals retired directly from full-time work. Retirement is defined as the first transition in which an individual claims a retirement benefit and reports zero working hours in the current year, having reported positive hours in the previous year.

Figure 3 further shows that almost 60% of men retire abruptly, compared with only about 20% of women. However, Figure 4 reveals that women retire from jobs with an average workload of more than 20 hours per week, indicating that their transition also involves a substantial reduction in working hours.

These stylized facts raise the question of what drives these retirement patterns, and in particular the abrupt transitions that many individuals exhibit. Are they primarily the result of workers' preferences, that is, supply-side factors? Or do they reflect demand-side frictions, such as firms' reluctance to hire older workers in part-time positions? The documented distinct labor supply patterns over gender also suggest that allowing for heterogeneity in the parameters that govern labor market behavior over gender is potentially important. Institutional factors, such as the design of the pension system, may also play an important role in shaping labor market outcomes. We present a model that allows us to disentangle these mechanisms.

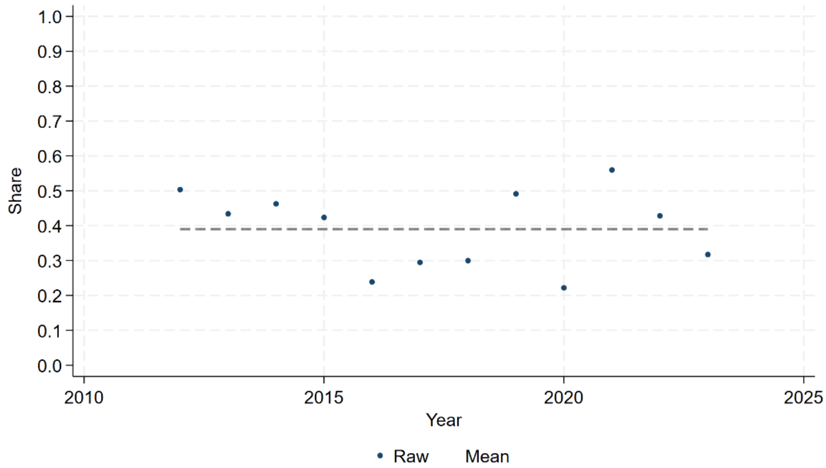


Figure 2: Share retiring from full-time work. The measure includes individuals who claim a retirement benefit and report zero hours in the current year, provided they reported positive hours in the previous year. Only the first such transition per person is counted.

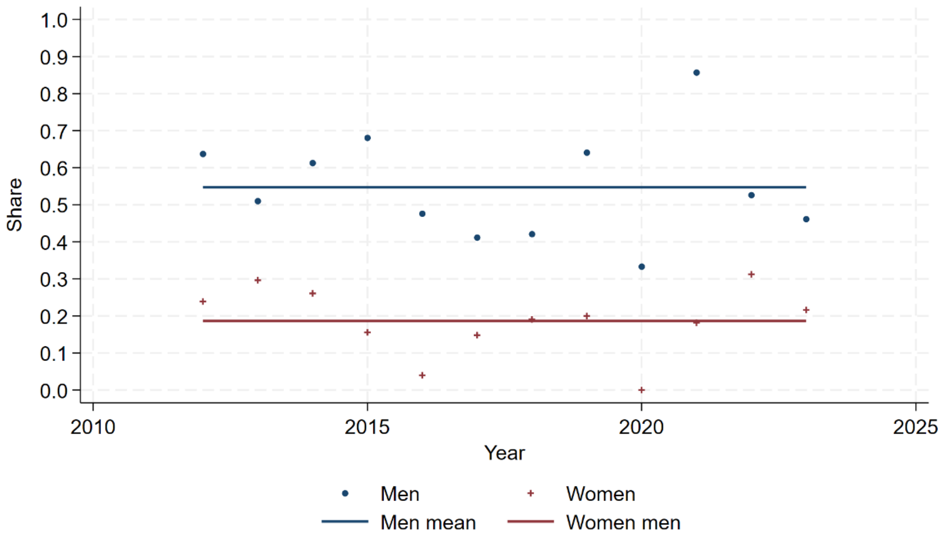


Figure 3: Share retiring from full-time work by gender. The measure includes individuals who claim a retirement benefit and report zero hours in the current year, provided they reported positive hours in the previous year. Only the first such transition per person is counted.

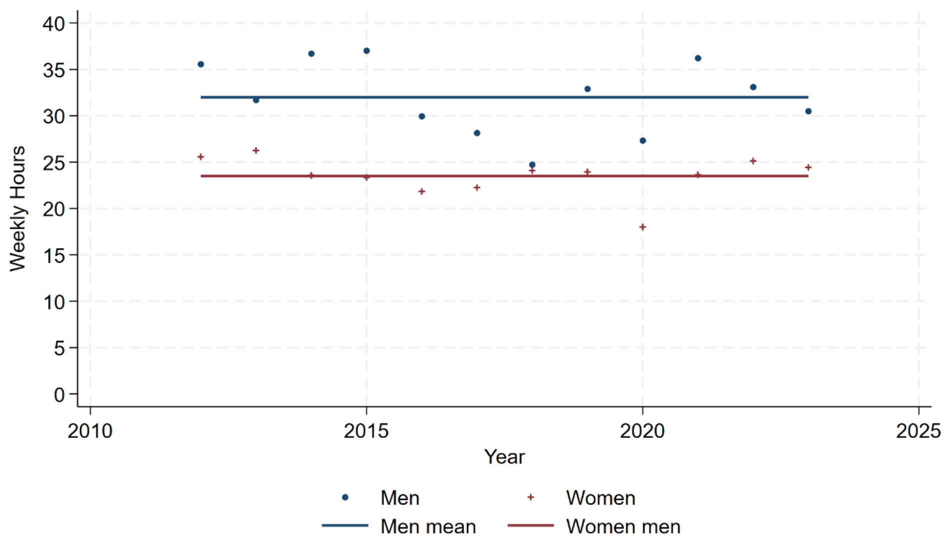


Figure 4: Hours individuals retire from. The measure includes individuals who claim a retirement benefit and report zero hours in the current year, provided they reported positive hours in the previous year. Only the first such transition per person is counted.

3 Survey Design and Measurement

Our empirical strategy relies on reservation wages and willingness-to-pay (WTP) measures that are not observable in administrative or standard survey data. To obtain these objects, we fielded a tailored module in the LISS panel that places respondents in realistic job-choice scenarios linked to their own work histories. The module provides respondent-specific information on working hours, job amenities, and the compensation required to accept alternative job arrangements.

This section describes how these data are collected and how the resulting variables are defined and measured for use in our empirical analysis.

3.1 Survey

The survey was fielded in May 2025 as an add-on to the LISS panel administered by Centerdata at Tilburg University. The LISS is a representative, long-running longitudinal survey of Dutch households, allowing our module to be linked to rich background information such as demographics, assets, and pension entitlements. The survey targeted individuals aged 45–75 and achieved a response rate of 70%, yielding 2,371 respondents.

The objective of the module is to measure willingness to pay (WTP) for key job amenities among prime-aged and older workers. While hours of work are our primary focus, the module also varies job flexibility, stress, and physical demands. Unlike discrete-choice experiments that recover only relative preferences, SSQs directly elicit reservation wages for jobs with specific characteristics, providing cardinal measures of the value of job amenities.

Reference Job Each respondent was first placed in a personalized *reference job*, either their current job (if employed) or their longest past job (if not currently working).[2] We collected information on weekly hours $h^{week}_{i,ref}$, annual earnings $y^{earn}_{i,ref}$, and characteristics such as flexibility, stress, and physical demands. Respondents verified the information in a summary table before proceeding; an example is shown in Table 1.

Characteristics	**Your answers**
Annual earnings	60,400 euro
Regular hours worked	38 hours per week The job is a full-time job
Degree of physical demand	Low or moderate
Stress level	Medium, low, or none
Flexibility (schedule/workplace) Most important flexibility	Some flexibility Setting start/end times

Table 1: Job Characteristics Table (example)

Strategic Survey Questions (SSQs) After defining the reference job, respondents answered SSQs designed to elicit reservation wages for jobs differing in one dimension at a time. All SSQs placed respondents in a hypothetical but realistic situation:[3]

> Imagine that your current job ends suddenly, but it does not affect your chances of finding future work. The only change is that you can no longer stay in your current position.
>
> In the upcoming scenarios, you will choose between Option A and Option B:
>
> - **Option A**: Accept a specific job offer right away. This offer is available only for a short period (e.g., one week) and will not return.
> - **Option B**: Explore other options, such as looking for a different job or choosing not to work.

[2] Respondents who had never worked for an employer were asked about a hypothetical job suited to them.

[3] Example wording applies to respondents who were currently employed.

Option A always matched the reference job in all but one characteristic. When hours changed, the hourly wage was held fixed so that annual earnings scaled proportionally.

After respondents chose either to accept the job (Option A) or decline it (Option B), we asked them for their reservation wage conditional on that choice. For respondents who accepted the job, the reservation wage question read:

> Suppose the annual salary for Option A were reduced. What is the lowest salary you would still accept for Option A before switching to Option B? The slider below starts at the salary of the reference job, adjusted for the reduced number of hours. Move the slider to the lowest amount at which you would still choose Option A. If you leave the slider at the amount of [RJ_SALARY], this indicates that you would switch to Option B for any reduction of your salary.

The slider displayed both the implied annual salary (proportionally adjusted) and the hourly wage, allowing respondents to judge the extent of non-proportionality when adjusting the salary.

Respondents who declined the job offer (Option B) were instead asked to imagine that the annual salary for Option A increased. The slider started at the hours-adjusted salary and could be raised to twice the annual salary. Respondents could also check a box indicating that they would never take the job at any wage.[4] We used two SSQs for the analysis in this paper:

- **SSQ 1:** Option A equals the reference job.
- **SSQ 2:** Option A differs only in weekly hours, allowing us to measure preferences for part-time versus full-time work.

If the reference job was part-time ($h^{week}_{i,ref} < 36$), Option A offered a full-time job (38 hours) in SSQ 2. If the reference job was full-time, Option A offered a part-time job (32 or 24 hours). All other job attributes were held constant.[5]

We implemented two scenarios. Employed respondents and half of the non-working sample were asked "What would you do today?" using their current job as the refer-

[4] In a pilot study, many respondents selected this option early. In the final survey, we therefore added a second, larger slider with an upper bound of ten times the annual salary, shown only if respondents refused the job at the two-times upper bound. Only after this second slider appeared could respondents indicate that they would never accept the job. Most respondents, however, did not use this second slider and instead directly chose "never accept." This is shown in the frequency tables in Appendix F.

[5] Respondents also answered SSQs on flexibility, stress, and physical demands, which we do not analyze here.

ence job. The remaining non-workers were assigned to a retrospective scenario based on the end of their longest past job.

3.2 Construction of Model Variables

Reservation wage–hours pairs From SSQ1 and SSQ2 we observe reservation wages for two job offers per individual: the reference job and a job with altered hours. Let w_i^{ref} denote the hourly wage in the reference job and $h_{i,ref}^{week}$ the associated hours. SSQs yield reservation wages (in percent of w_i^{ref}) for:

$$(w_{i,rw}^{ref}, h_{i,ref}^{week}) \qquad \text{and} \qquad (w_{i,rw}^{SSQ2}, h_{i,SSQ2}^{week}).$$

Stacking these two observations gives a reservation-wage–hours pair

$$(w_{i,rw}, h_{i,rw}^{week})$$

for each available hours level.

Other characteristics We assign respondents' state variables at the date relevant for their SSQ scenario: either the survey date (for current workers) or the end of the longest past job (for a subset of non-workers). These state variables include scenario age, age_i^{sce}, defined as the age at which the respondent is assumed to be making the choice depicted in the stated preference scenario, net assets netass_i, pension entitlements pens_i, partnership status partnered_i, and education category educ3_i.[6] Some older non-workers lack asset and pension data at the scenario date; missing values are imputed as described in Appendix E.

Estimating Data Moments for the First Stage Survey respondents report their reservation wage using a slider, with values censored at 200% of their reference wage w_i^{ref}. To capture how reservation wages vary with weekly hours, age, and gender, we estimate the following Tobit model:

$$\begin{aligned} w_{i,rw} \quad = \quad & f\big(h_{i,rw}^{\text{week}}, (h_{i,rw}^{\text{week}})^2, \text{age}_i^{\text{sce}}, \text{female}_i, \\ & h_{i,rw}^{\text{week}} \times \text{age}_i^{\text{sce}}, h_{i,rw}^{\text{week}} \times \text{female}_i, \text{age}_i^{\text{sce}} \times \text{female}_i\big) \ + \ X_i'\beta + \varepsilon_i, \end{aligned} \tag{1}$$

[6] Education categories follow Dutch qualifications: (i) Basisonderwijs, VMBO, LBO/LTS = low; (ii) HAVO, VWO, MBO = medium; (iii) HBO and WO = high.

with censoring at $w_{i,rw} \leq 200\%$. The vector X_i includes net assets, pension entitlements, partnership status, and education.

Using these estimates, we construct predicted reservation wages

$$\widehat{w}_{rw}(h^{\text{week}} \,|\, \text{age, gender}), \qquad h^{\text{week}} \in [15, 45],$$

evaluated at the sample mean of $\overline{X}$, for selected ages and separately by gender.

We then compute the corresponding willingness to pay (WTP) for reducing weekly hours by ten:

$$\text{WTP}_{10}(h^{\text{week}}, \text{age}, \text{gender}) = \widehat{w}_{rw}(h^{\text{week}} \,|\, \text{age}, \text{gender}) - \widehat{w}_{rw}(h^{\text{week}} - 10 \,|\, \text{age}, \text{gender}), \tag{2}$$

which represents the compensating variation required for an individual to accept a reduction from h^{week} to $h^{\text{week}} - 10$ hours.

4 Empirical Moments: Reservation Wages and WTP

We begin by summarizing the main empirical objects that inform our structural estimation: the reservation-wage schedules implied by respondents' stated preferences, and the resulting willingness-to-pay (WTP) profiles for reducing working hours.

Throughout the analysis we rely on the survey sample for which all variables required in the empirical specification are observed or can be imputed. In particular, we use only respondents for whom net assets and pension entitlements at the scenario date can be recovered from the longitudinal LISS panel. This sample consists of 1,622 individuals and is the effective dataset used in all subsequent empirical exercises.

Descriptive statistics for this sample, as well as a comparison to the full group of survey respondents, are reported in Appendix F. The estimation sample is somewhat younger and more likely to be employed, reflecting the availability of asset and pension information, but otherwise similar in its demographic composition.

We now turn to the two central survey-based objects: reservation wages for jobs with different working hours, and the willingness to pay (WTP) for reducing hours.

4.1 Reservation Wages

Figure 5 presents the predicted reservation-wage schedules from the Tobit model in equation (1). The gender differences are stark. For women, reservation wages rise steeply with weekly hours: at 15 hours per week, predicted reservation wages already exceed 130% of the reference-job wage and rise to roughly 180% at 45 hours. Older women (age 65) have uniformly higher reservation wages than women age 55, producing an upward shift of the entire profile.

Male reservation wages, by contrast, display a more nuanced pattern. Figure 6 depicts the male profiles on a separate scale to clarify these subtler dynamics. Men age 55 exhibit a downward-sloping reservation-wage schedule, indicating a preference for full-time employment over part-time employment. However, as men grow older, this schedule begins to take on a U-shape: older men demand increasingly higher reservation wages for both full-time and low part-time hours, while mid-range part-time schedules become relatively more attractive. Notably, men never appear to value very low part-time hours, even later in life. These findings reveal a distinct and informative sensitivity of male reservation wages to hours and age—very different in shape from the consistently upward-sloping patterns observed for older women.

Reservation wages above 100% indicate that respondents require an hourly wage exceeding the reference-job wage to accept the offered job. This may reflect that in our survey Option A fixed all non-wage job characteristics until retirement and allowed adjustments to hours only after one year, reducing flexibility relative to some respondents' actual jobs.

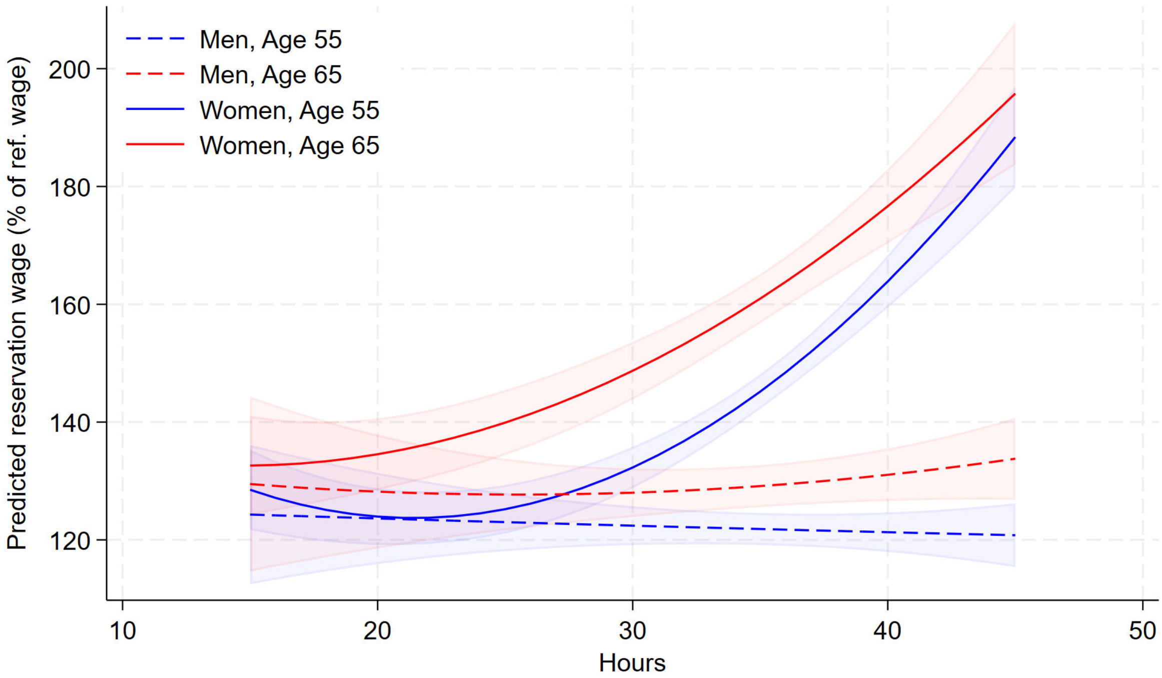


Figure 5: Predicted Reservation-Wage Schedules by Gender and Age. Reservation wages predicted from the Tobit model in equation (1), expressed as a percentage of the reference-job hourly wage. Curves shown for ages 55 and 65 for men and women in the restricted sample. Shaded areas represent 90% confidence bands.

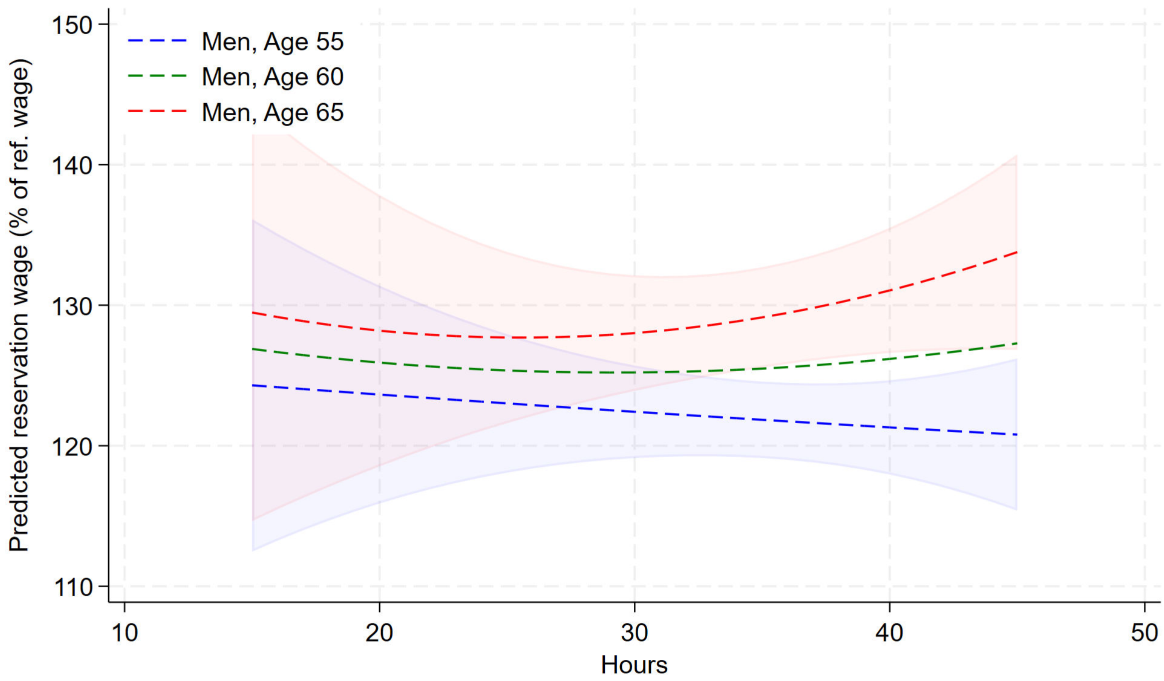


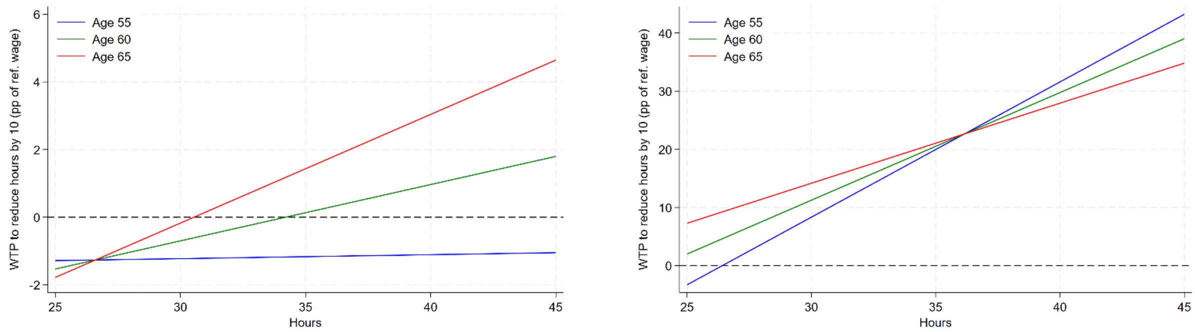
Figure 6: Predicted Reservation-Wage Schedules of Men. Reservation wages predicted from the Tobit model in equation (1), expressed as a percentage of the reference-job hourly wage. Curves shown for ages 55, 60 and 65 for men. Shaded areas represent 90% confidence bands.

4.2 Willingness to Pay (WTP) for Reducing Hours

Figure 7 displays the implied willingness to pay (WTP) to reduce weekly hours by ten, computed using the predicted reservation-wage schedules and equation (2).

For men at age 55, the WTP is negative at most hour levels and nearly flat. For older men, the WTP profile becomes increasingly steep. A 65 year old man is willing to accept a roughly 3% wage reduction to reduce hours worked from 40 to 30, whereas a 55 year old man would require a 1.5% wage increase for the same reduction. At sufficiently low hours, the WTP becomes negative even for older men, indicating little value placed on additional reductions once they work well below full-time.

Panel (b) of Figure 7 shows a markedly different pattern for women. WTP increases sharply with weekly hours and reaches 25–30% at 40 hours per week. Age differences are modest and primarily visible at hours below 36, where older women display a somewhat higher WTP than younger women. Overall, women exhibit a substantially stronger preference for reducing hours than men, especially at higher hours levels.



(a) Men **(b)** Women

Figure 7: Willingness to Pay to Reduce Weekly Hours by 10, by Age and Gender. WTP calculated as the difference in predicted reservation wages between weekly hours h and $h-10$ as in equation (2). Positive values indicate willingness to accept a wage reduction (in percentage points of reference-job wage) in exchange for fewer hours.

5 Static Model for Intuition

This section presents a simple static labor supply model to illustrate the challenge of separately identifying labor supply and labor demand factors, and shows how stated reservation wages for different hours choices can overcome this challenge.

Labor Supply Side Factors Households choose hours worked $h \in [0,1]$ to maximize the utility function $u(c,h)$ featuring constant relative risk aversion (CRRA) and separability in consumption and hours worked:

$$u(c,h) = \underbrace{\frac{c^{1-\frac{1}{\rho}}-1}{1-\frac{1}{\rho}}}_{\text{CRRA utility over consumption}} - \underbrace{\phi\frac{h^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}}}_{\text{Disutility from working}}.$$

Here, the toy model's supply-side parameters are

$$\Omega^{D}_{tm} = \{\phi, \gamma, \rho\}.$$

The parameter ρ with $\rho \neq 1$ governs risk aversion, ϕ captures the disutility of working (that is, the taste for leisure), and γ determines the labor supply elasticity and how quickly the disutility of work rises with hours. In a dynamic setting, ρ also governs the strength of consumption smoothing, and γ the intertemporal elasticity of labor supply, that is, the desire to smooth working hours and leisure over time.

Labor Demand Side Factors Frictions on the firm side, or a limited willingness to offer schedules that match the preferences of workers, imply that hourly wages are nonlinear. This generates a part-time wage penalty summarized by the parameter $\theta \geq 0$. Consequently, labor income y^{earn} depends on full-time-equivalent hours worked h according to:

$$y^{\text{earn}} = \underbrace{w \cdot h^{\theta}}_{\text{Hourly Wage}} \cdot h,$$

where w defines earnings potential at full-time, which here is $h = 1$. The demand-side component can therefore be summarized by $\Omega^D_{tm} = \{\theta\}$, where the effective hourly wage satisfies $w \cdot h^{\theta} \leq w$.

The Household Problem Household i solves the problem:

$$\max_{h_i} u(c_i, h_i) \quad s.t. \quad c = \underbrace{(w_i \cdot h_i^{\theta}) \cdot h_i}_{y^{\text{earn}}} + a_i, \tag{3}$$

where a_i denotes non-labor income. The first order condition yields:

$$(1+\theta)\, w_i h_i^{1+\theta} \left(\underbrace{w_i h_i^{1+\theta} + a_i}_{c_i} \right)^{-\frac{1}{\rho}} = \phi\, h_i^{\frac{1}{\gamma}} \tag{4}$$

The left-hand side represents the marginal utility gain from working an additional unit of time, given by the marginal increase in earnings multiplied by the marginal utility of consumption. The right-hand side represents the marginal disutility of working an extra hour.

5.1 Identification Challenge

Since the FOC in (4) contains both supply-side and demand-side determinants, the optimal hours choice $h_i^*(\Omega^S_{tm}, \Omega^D_{tm})$ is jointly determined by both sets of parameters. For the special case with no non-labor income ($a_i = 0$), the FOC can be solved in closed form, yielding[7]

$$h_i^*(\Omega^S_{tm}, \Omega^D_{tm}) = \left(\frac{(1+\theta)\, w_i^{1-\frac{1}{\rho}}}{\phi} \right)^{\frac{1}{\frac{1}{\gamma} - \theta + \frac{1}{\rho}}}.$$

The expression for h_i^* highlights the fundamental identification problem: market hours reveal only the composite outcome of supply-side preferences Ω^S_{tm} and demand-

[7] An interior solution requires $D \equiv \frac{1}{\gamma} - \theta + \frac{1}{\rho} > 0$.

side constraints Ω^{D}_{tm}. For instance, low observed h_i may reflect a high disutility of work (ϕ), rapidly increasing disutility with hours (γ), or a strong part-time wage penalty (θ).

In what follows—including later when we introduce the dynamic quantitative model, which builds on this static framework—we focus on identifying the two key supply-side parameters governing the disutility of work and the labor supply elasticity,

$$\Omega^{S}_{tm} = \{\phi, \gamma\},$$

and the demand-side parameter capturing the part-time wage penalty,

$$\Omega^{D}_{tm} = \{\theta\},$$

while treating all remaining preference parameters as known from the literature. In the static model, this implies that the curvature parameter ρ is taken as given.

Proposition 1. *Even with complete information on market outcomes $\{h^*_i, y^{earn}_i, a_i\}_{i=1}^{N}$ and knowing ρ, the structural supply-side parameters $\Omega^{S}_{id,tm} = \{\phi, \gamma\}$ and the demand-side parameter $\Omega^{D}_{tm} = \{\theta\}$ cannot be separately identified.*

Proof: See Appendix A.

5.2 Identification via Reservation Wages

Next, we illustrate how eliciting reservation wages allows us to separately identify the structural supply-side parameters $\Omega^{S}_{id,tm} = \{\phi, \gamma\}$ and the demand-side parameter $\Omega^{D}_{tm} = \{\theta\}$. The outside option is not working ($h = 0$), yielding utility:

$$u(a_i, 0) \;=\; \frac{a_i^{1-\frac{1}{\rho}} - 1}{1 - \frac{1}{\rho}}. \tag{5}$$

For any $h > 0$, the reservation wage $w_r(h)$ is defined by indifference between working and not working:

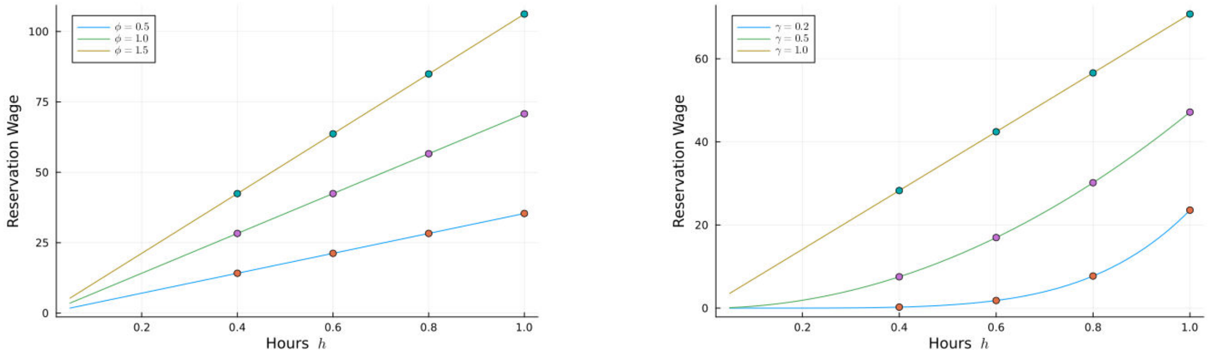
$$u(w_r(h)\, h + a_i, h) \;=\; u(a_i, 0). \tag{6}$$

Rearranging with $\kappa \equiv 1 - \frac{1}{\rho}$ yields

$$(w_r(h)\, h + a_i)^{\kappa} - a_i^{\kappa} \;=\; \kappa\, \phi\, \frac{h^{1+\frac{1}{\gamma}}}{1 + \frac{1}{\gamma}} \quad \Longrightarrow \quad w_r(h) = \frac{\left(\kappa\, \phi \frac{h^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} + a_i^{\kappa}\right)^{\frac{1}{\kappa}} - a_i}{h}. \tag{7}$$

Equation (7) illustrates how reservation wages embody preferences over work and leisure. As shown in Panel (a) of Figure 8, a higher ϕ requires greater compensation for any $h > 0$. Increasing ϕ rotates the reservation-wage schedule upward around the origin.

The parameter γ governs how rapidly the marginal disutility of labor increases with hours. A small γ produces a sharply convex schedule, while a large γ yields a more linear one. Thus, variation in reservation wages across hours identifies γ.



(a) Varying ϕ **(b)** Varying γ

Figure 8: Reservation-wage schedules $w_r(h)$ under different preference parameters.

Proposition 2 (Identification). *Suppose ρ is known. If reservation wages $w_r(h)$ are observed at two distinct positive hour levels for at least two individuals, and market earnings y_i^{earn} are observed at a chosen hour, then the structural supply-side parameters $\Omega^S_{id,tm} = \{\phi, \gamma\}$ and the demand-side parameter $\Omega^D_{tm} = \{\theta\}$ are separately identified.*

Proof. Apply (7) at full-time and part-time hours $h_i^{ft} > h_i^{pt} > 0$ and define

$$\Delta_i \equiv (w_r(h_i^{ft})h_i^{ft} + a_i)^\kappa - (w_r(h_i^{pt})h_i^{pt} + a_i)^\kappa = \kappa\,\phi\,\frac{(h_i^{ft})^{1+\frac{1}{\gamma}} - (h_i^{pt})^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}}.$$

Taking the ratio for two individuals A and B eliminates ϕ:

$$\frac{\Delta_A}{\Delta_B} = \frac{(h_A^{ft})^{1+\frac{1}{\gamma}} - (h_A^{pt})^{1+\frac{1}{\gamma}}}{(h_B^{ft})^{1+\frac{1}{\gamma}} - (h_B^{pt})^{1+\frac{1}{\gamma}}}. \tag{8}$$

The right-hand side is strictly monotone in γ, so this identifies γ. Substituting back identifies

$$\phi = \frac{1+\frac{1}{\gamma}}{\kappa} \cdot \frac{\Delta_A}{(h_A^{ft})^{1+\frac{1}{\gamma}} - (h_A^{pt})^{1+\frac{1}{\gamma}}}.$$

Given (ϕ, γ), the FOC in earnings satisfies

$$(1+\theta)\,y_i^{\text{earn}}\left(y_i^{\text{earn}} + a_i\right)^{-\frac{1}{\rho}} = \phi\,h_i^{\frac{1}{\gamma}},$$

the left-hand side of which is strictly increasing in θ, yielding a unique θ. Thus, $\Omega^S_{id,tm} = \{\phi, \gamma\}$ and $\Omega^D_{tm} = \{\theta\}$ are separately identified. $\square$

Connecting it back to the dynamic model. In the full dynamic model, these same preference parameters (ϕ_t, γ), where the weight on the disutility from work ϕ_t varies now by age, shape the value of working at different hours and ages, entering individuals' optimal labor-supply and retirement decisions through the choice-specific value functions. While savings behavior, survival risk, and pension incentives add dynamic considerations, the underlying identification mechanism remains the same: age-specific shifts in ϕ_t determine the general level of willingness to work, whereas γ governs how sharply the disutility of work rises with hours. Hence, the static model provides the key intuition for how reservation-wage data—through their implied indifference conditions between full-time and part-time work—identify the supply-side preference parameters in the quantitative framework.

6 Quantitative Model

In this section, we present the full quantitative model. Time (age) in the model is discrete and indexed by t. Agents live for up to T periods. The individual survival probability between periods t and $t+1$ is denoted by $\psi_t \in (0, 1)$.

6.1 Choices

Agents enter the model at age 50 as employed or unemployed workers. They face a continuous consumption choice c_t, subject to a borrowing constraint, and discrete choices d_t over the following two dimensions: yearly hours worked $h_t \in \{0, 0.4, 0.24, 0.16\}$ and claiming of occupational pensions $op_t \in \{0, 1\}$. Table 2 summarizes the available choices $d_t \in \mathcal{D}$.

Table 2: Choice set $\mathcal{D}$

d_t	h_t^{yearly}	h_t	h_t^{fte}	op_t	Comment
1	0	0	0	0	Unemployed
2	2000	0.4	1	0	Full-time worker
3	1600	0.32	0.8	0	Part-time worker
4	1200	0.24	0.6	0	Part-time worker
5	800	0.16	0.4	0	Part-time worker
6	2000	0.4	1	1	Partial retiree
7	800	0.16	0.4	1	Partial retiree
8	0	0	0	1	Full-time retiree

In accordance with Dutch legislation, claiming occupational pensions ($op_t = 1$) is an absorbing state that is possible after reaching age 62. This means that once an individual begins receiving occupational pension benefits, they remain in that state permanently and cannot suspend or postpone payments. Furthermore, we assume that once pensions are claimed, individuals can no longer increase hours. For simplicity, we assume that all individuals are required to claim their occupational pension no later than age 75. Finally, we assume that everyone has fully retired ($h_t = 0, op = 1$) by 80.

Individuals' choices are influenced by two endogenous state variables: cash-on-hand m_t and the stock of pension accruals pw_t.

6.2 Institutions

There are three tax and transfer systems: unemployment insurance (UI), pensions, and a progressive income tax.

The law of motion for pension accruals, denoted by pr_t, is given by:

$$pr_{t+1} = pr_t + 0.0205 \cdot \max\left(y_{t+1}^{\text{earn}} - 18000,\, 0\right),$$

where y_{t+1}^{earn} denotes labor earnings. From age $t = 62$ onward, individuals endogenously claim pension benefits, which are defined as:

$$\text{Pens}_{t+1} = (pr_t + 18000) \cdot AcAdj_{t_{op}} \cdot \left(1 - h_{t+1}^{\text{fte}}\right),$$

where $AcAdj_{t_{op}}$ represents the actuarial adjustment factor. For simplicity, we assume that $AcAdj_t = 1$. In reality, this factor is an increasing function of the age, t_{op}, at which pensions where claimed for the first time.

Individuals who provide no working hours and have not yet claimed pension benefits ($op_t = 0$), receive an unemployment benefit UI_t, which for simplicity is equal to a flat amount B^{UI} for now.

In addition, the government collects a total tax Tax_t^{total}, which is described in Appendix B.

6.3 Labor Demand Side Factors

In line with the static model, we assume that frictions at firms generate nonlinear hourly wages, i.e., a part-time wage penalty governed by the parameter $\theta \geq 0$. Consequently, labor income y_t^{earn} depends on full-time-equivalent hours worked h_t^{fte} according to:

$$y_{t+1}^{\text{earn}} = \left(w_{o,t+1} \cdot (h_t^{\text{fte}})^{\theta}\right) h_t^{\text{fte}},$$

where $w_{o,t+1}$ is the earnings potential for full-time hours at age $t+1$. The demand-side component in the quantitative model is again summarized by $\Omega^D = \{\theta\}$, which governs the extent of the part-time penalty. Accordingly, the effective hourly wage for an older worker in period $t+1$ satisfies

$$w_{o,t+1} \cdot (h_t^{\text{fte}})^\theta \leq w_{o,t+1},$$

with equality if and only if the individual supplies full-time equivalent hours ($h_t^{\text{fte}} = 1$).

6.4 Labor Supply Side Factors

As usual, agents make decisions to maximize expected lifetime utility U_t, which itself depends on an instantaneous utility function $u(c_t, h_t)$ of the MaCurdy (1981) type with constant relative risk aversion and separable in consumption and hours worked:

$$u(c_t, h_t) = \underbrace{\frac{c_t^{1-\frac{1}{\rho}} - 1}{1 - \frac{1}{\rho}}}_{\text{CRRA utility over consumption}} - \underbrace{\phi_t \frac{h_t^{1+\frac{1}{\gamma}}}{1 + \frac{1}{\gamma}}}_{\text{Disutility from working}}.$$

The utility function is age-specific, reflecting the fact that the disutility of work parameter ϕ_t is allowed to vary with age in the dynamic model. At any age t, the expected lifetime utility of an individual is then given by

$$U_t = \mathbb{E}_t \left[\sum_{\tau=t}^{T} \beta^{\tau-t} \prod_{j=t-1}^{\tau-1} \psi_t \cdot \left(\frac{c_t^{1-\frac{1}{\rho}} - 1}{1 - \frac{1}{\rho}} - \phi_t \frac{h_t^{1-\frac{1}{\gamma}} - 1}{1 - \frac{1}{\gamma}} \right) \right] \tag{9}$$

Utility depends on a set of preference parameters that define the five **labor supply-side factors**, denoted by $\Omega^S = \{\phi_t, \gamma, \rho, \beta\}$. Here, γ governs the intertemporal elasticity of substitution in labor supply, $\phi_t \equiv \phi_0 + \phi_1 \cdot t$ represents the marginal rate of substitution between consumption and leisure, ρ governs intertemporal consumption smoothing, and β is the subjective discount factor. Labor supply-side parameters are further divided into those that are set exogenously, $\Omega^S_{exo} = \{\rho, \beta\}$, and those that are estimated, $\Omega^S_{est} = \{\phi_0, \phi_1, \gamma\}$, such that $\Omega^S = \{\Omega^S_{exo}, \Omega^S_{est}\}$.

6.5 Individual Decision Problem

As mentioned, individuals maximize expected utility as defined in equation 9, which can be represented by the value function V_t. The value function of an individual of age t with current state variables of cash-on-hand, m_t, and pension accruals, pr_t, is given by:

$$V_t\left(m_t, pr_t|\Omega^D, \Omega^S\right) = \max_{d_t \in \mathcal{D}} \left\{ v_t\left(m_t, pr_t, d_t|\Omega^D, \Omega^S\right) + \lambda\epsilon\left(d_t\right)\right\}$$

where $v_t\left(m_t, pr_t, d_t|\Omega^D, \Omega^S\right)$ is a choice-specific value function over consumption for a given choice, d_t. Discrete labor choices generally introduce kinks in the value function and jumps in the policy function, propagating backward in time. Because of these kinks, there are multiple solutions to the Euler equation. Consequently, we use the Discrete-Choice Endogenous Grid Method (DC-EGM), see Iskhakov et al. (2017). This is an extension of the Endogenous Grid Method to a setting with a discrete labor choice, see Carroll (2006).

Although the solution method can handle non-convexities and multiple solutions to the Euler equation, we also consider a type-1 extreme-value taste shock, $\epsilon\left(d_t\right)$, with scale parameter, λ. As shown in McFadden (1973), the taste shock acts as a logit smoother of value functions by making labor choices probabilistic. For our purposes, the taste shock represents unobserved factors of individual choices and permits a smoother transition into retirement, providing a better model fit. The choice-specific value function can be written in the following recursive form:

$$v_t\left(m_t, pr_t, d_t|\Omega^D, \Omega^S\right) = \max_{a_t \geq 0} \frac{c_t^{1-\frac{1}{\rho}} - 1}{1-\frac{1}{\rho}} - \phi_t \frac{h_t^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} + \beta \cdot \psi_t \cdot \mathbb{E}_t[V_{t+1}(\cdot)]$$

$$\begin{aligned}
&\text{s.t.}\\
m_t &= a_t + c_t\\
y_{t+1}^{earn} &= \left(w_{o,t+1} \cdot \left(h_t^{\text{fte}}\right)^{\theta}\right) h_t^{\text{fte}}\\
pr_{t+1} &= pr_t + 0.0205 \cdot \left(\max\left[y_{t+1}^{earn} - 18000\right]\right)\\
Pens_{t+1} &= \left[pr_t + 18000\right] \cdot AcAdj_t \cdot \left(1 - h_{t+1}^{\text{fte}}\right)\\
m_{t+1} &= y_{t+1}^{earn} + B^{UI}\mathbb{I}_{d_t=1} + Pens(.)\mathbb{I}_{d_t \geq 6} + Ra_t - Tax_{t+1}^{total},
\end{aligned}$$

where a_t denotes savings, $\mathbb{I}_{d_t=1}$ is an indicator function equal to one if the individual is unemployed ($d_t = 1$), and $\mathbb{I}_{d_t \geq 6}$ is an indicator equal to one if the individual is claiming pension benefits.

It is straightforward to derive the first-order condition for optimal consumption

$$c_t^{-\frac{1}{\rho}} = \beta \cdot \psi_t \cdot R \cdot \mathbb{E}_t^{\lambda^{\varepsilon}}\left[c_{t+1}^{-\frac{1}{\rho}}\right]$$

As the first-order condition shows, evaluating expectations over future choices and values is essential. Appendix D illustrates how we approach this.

6.6 Identification

As discussed above, labor and consumption–saving decisions in the model are jointly determined by the demand-side parameters Ω^D and the supply-side parameters Ω^S. Following the intuition from the static model, standard structural estimation strategies that rely solely on observed life-cycle profiles of labor supply and consumption cannot separately identify these two parameter sets, because supply-side preferences and demand-side frictions affect observed behavior in similar ways.

To disentangle supply-side preferences from demand-side frictions, we use stated preference data to recover reservation-wage schedules for different working hours, ages, and genders. As described in Section 4, we estimate a Tobit model and obtain predicted reservation wages

$$\widehat{w}_{rw}(h^{\text{week}} \mid \text{age, gender, } X),$$

expressed as a percentage of the respondent's reference-job wage. Here, X denotes the set of conditioning variables in the Tobit regression, including net assets and pension entitlements matched to the model state variables (m_t, pr_t).

For each $(\text{age}, \text{gender}, X)$ cell and each weekly hours level h^{week} in the survey, the quantity $\widehat{w}_{rw}(h^{\text{week}} \mid \text{age}, \text{gender}, X)$ represents the wage level at which a representative individual is just indifferent between accepting a job with weekly hours h^{week} and not working.

Mapping to model hours. The quantitative model features a discrete set of working-hour choices in full-time–equivalent hours:

$$h^{\text{fte}} \in \{1, 0.8, 0.6, 0.4\},$$

corresponding to the choice alternatives $d_t \in \{2, 3, 4, 5\}$ for individuals not yet claiming occupational pensions. Since almost all respondents in the SSQ scenarios fit this case, we restrict attention to this subset of choices.

For each model hours level h^{fte} and each (t, gender, X) cell, we assign an *annual* reservation wage via:

$$\widehat{w}_{rw}^{\text{job}}(t, \text{gender}, X) = \widehat{w}_{rw}\big(h^{\text{week}}(h^{\text{fte}}) \mid t, \text{gender}, X\big) \cdot \mathcal{A},$$

where $h^{\text{week}}(h^{\text{fte}})$ maps the model's full-time–equivalent hours to weekly hours in the survey (e.g., $h^{\text{fte}}{=}1$ maps to 38 hours, $h^{\text{fte}}{=}0.6$ maps to 24 hours). The scalar

$$\mathcal{A} \equiv 46 \cdot h^{\text{week}}(h^{\text{fte}})$$

converts the hourly reservation wage into an annual amount, assuming 46 working weeks per year.[8]

Indifference conditions between full-time and part-time options. For each (t, gender, X) cell, we treat the full-time option ($h^{\text{fte}} = 1$ or $d_t = 2$) as the reference and use the predicted reservation-wage schedule to construct indifference conditions between the full-time and part-time model options $d_t \in \{3, 4, 5\}$.

For a given age t, gender g, and state (m_t, pr_t) implied by X, the SSQ information implies that, when paid at their respective reservation wages:

$$v_t\Big(m_t, pr_t, d_t^{\text{ft}} = 2 \,\big|\, \widehat{w}_{rw}^{\text{ft}}(t, g, X), \Omega^S\Big) = v_t\Big(m_t, pr_t, d_t^{\text{pt}} \,\big|\, \widehat{w}_{rw}^{\text{pt}}(t, g, X), \Omega^S\Big), \tag{10}$$

where superscripts "ft" and "pt" indicate that the wage is evaluated at the full-time or part-time hours level via the mapping from $\widehat{w}_{rw}(\cdot)$.

Equation (10) states that the representative individual of type (t, g, X) is indifferent between full-time and a particular part-time option (say, $d_t = 3$) when both are compensated at their respective reservation wages. Since these reservation wages are taken from the empirical schedule and enter the model as exogenous job offers in the SSQ environment, these indifference relations depend only on the supply-side parameters Ω^S and not on the demand-side parameter θ.

To see formally why the indifference conditions in (10), which we target in our estimation described in the next section, depend only on Ω^S, note that the choice-specific value function for any $d_t \in \{2, 3, 4, 5\}$ evaluated at the corresponding reservation wage satisfies:

$$v_t(m_t, pr_t, d_t \mid \widehat{w}_{rw}^{\text{job}}(t, g, X), \Omega^S) = \max_{a_t \geq 0} \left[\frac{c_t^{1-\frac{1}{\rho}} - 1}{1 - \frac{1}{\rho}} - \phi_t \frac{h_t^{1+\frac{1}{\gamma}}}{1 + \frac{1}{\gamma}} + \beta\, \psi_t\, \mathbb{E}_t V_{t+1}(\Omega_{t+1}) \right]$$

$$\begin{aligned}
\text{s.t.} \quad m_t &= a_t + c_t, \\
y_{t+1}^{earn} &= \widehat{w}_{rw}^{\text{job}}(t, g, X) \cdot h_{t+1}^{\text{fte}}, \\
pr_{t+1} &= pr_t + 0.0205 \cdot \max\left[y_{t+1}^{earn} - 18{,}000\right], \\
m_{t+1} &= y_{t+1}^{earn} + B^{UI}\mathbb{I}_{d_t=1} + Ra_t - Tax_{T+1}^{total}.
\end{aligned}$$

Crucially, the earnings term y_{t+1}^{earn} is pinned down by the assigned reservation wage and does *not* involve the market wage $w_{o,t+1} \cdot (h_t^{\text{fte}})^{\theta}$ governed by the demand-side parameter θ. Therefore, the utilities on both sides of (10) depend only on the supply-

[8] This number reflects the Dutch institutional context, which includes paid vacation, holidays, and standard work-weeks.

side parameters Ω^S and the empirically predicted reservation wages.

These indifference conditions are at the heart of our identification and estimation strategy: by selecting Ω^S such that equation (10) holds across all relevant (t, gender, X) cells and model hours choices, we isolate and estimate the supply-side preference parameters independently of θ. The corresponding moment conditions are detailed and used in the estimation strategy described in the next section.

7 Estimation and Results

To estimate the quantitative model, we first calibrate exogenous parameters and then employ a two-stage estimation strategy: the first stage identifies supply-side preference parameters, while the second stage estimates the demand-side factor governing part-time wage penalties.

7.1 Calibration of Exogenous Parameters

This section describes the calibration of model parameters that are fixed in advance of the structural estimation. Table 3 summarizes the full set of exogenously set model parameters.

We begin with the timing of the life cycle. Individuals enter the model at age $T_b = 50$ and can live up to a maximum age of $T_m = 100$, facing survival probabilities ψ_t governed by a Gompertz mortality curve calibrated to Dutch mortality. Consistent with the institutional setting for most cohorts in our sample, eligibility for public pension benefits begins at age $T_{r,c} = 67$, while occupational pensions can be claimed as early as age $T_{o,c} = 62$. The latest possible claiming age for any pension is set to $T_x = 75$.

Preferences are partly governed by parameters taken from the literature. The intertemporal elasticity of substitution in consumption is given by $\rho = 0.5$, and the subjective discount factor is set to $\beta = 0.98$, both standard in the macro and life-cycle literature. The idiosyncratic taste shock ε_t is scaled by the parameter $\lambda = 0.1$, in line with values used in recent structural life-cycle models.[9]

We adopt a stylized representation of the tax and transfer system. Total taxes Tax_t^{total} follow a progressive schedule consistent with Dutch legislation, as detailed in Appendix B. Unemployment benefits are captured by a flat annual amount $B^{UI} =$ 10,000 euro. Finally, the gross after-tax return on savings is set to $R = 1.03$, implying a

[9] See, for example, Bacher et al. (2025) for a similar calibration.

real net return of approximately three percent, which is in line with values commonly used in the quantitative macro literature.

Overall, this calibration anchors the model in key institutional and financial features of the Dutch economy, while keeping the main focus on the parameters that govern labor supply behavior and labor demand frictions, which are estimated in the following sections.

Table 3: Exogenous Parameters

Parameter	Description	Value	Source
Timing			
T_m	Maximum age of life	100	
T_b	Age at birth	50	
$T_{r,c}$	Eligibility age for public pensions	67	See text
$T_{o,c}$	Eligibility age for occupational pensions	62	Dutch legislation
T_x	Latest claiming age for pensions	75	
Preferences			
ρ	IES of consumption	0.5	From the literature
β	Subjective discount factor	0.98	From the literature
λ	Taste shock scaling parameter	0.1	
Demographics			
ψ_t	Survival probability between t and $t+1$		Gompertz Model
Taxes and Transfers			
Tax_t^{total}	Progessive Taxes	Appendix B	Dutch Legislation
B^{UI}	Unemployment benefit	10,000 EUR	
Prices			
R	Gross after-tax return	1.03	

Notes: The table reports all calibrated and estimated parameters used in the model.

7.2 Estimation of Supply-Side Parameters

The first stage estimates the preference parameters governing the disutility of work and the curvature of utility over hours worked, denoted by

$$\Omega^S_{est} = \{\phi_0, \phi_1, \gamma\}.$$

These parameters are identified from the indifference relations implied by the predicted reservation-wage schedules described in Section 6.6. Rather than using individual-level responses, we simulate these indifference conditions over a grid of *cells* defined by age t, gender g, state variables X, and model hours levels $h^{\text{fte}} \in \{1, 0.8, 0.6, 0.4\}$ representing full-time and part-time work.

For each $(t, g, X, h^{\text{fte}})$ cell (indexed by i), we define the model-implied utility difference between the full-time option ($d_t^{\text{ft}} = 2$) and the corresponding part-time option ($d_t^{\text{pt}} \in \{3, 4, 5\}$):

$$e_i(\Omega^S) = v_t\Big(m_t, pr_t, d_t^{\text{ft}} = 2 \,\big|\, \widehat{w}_{rw}^{\text{ft}}(t, g, X), \Omega^S\Big) \; - \; v_t\Big(m_t, pr_t, d_t^{\text{pt}} \,\big|\, \widehat{w}_{rw}^{\text{pt}}(t, g, X), \Omega^S\Big). \tag{11}$$

The identifying restriction implied by the stated preference information is simply:

$$e_i(\Omega^S) = 0 \quad \text{for each cell } i.$$

In practice, a collection of such cells is constructed by evaluating the predicted reservation-wage function $\widehat{w}_{rw}$ at the model's discrete hours levels and at selected ages (e.g., t=55, 60, 65), separately for men and women and for representative combinations of X. Stacking these cell-specific restrictions yields a system of moment conditions that depend only on the supply-side parameters Ω^S, forming the basis for the first-stage estimation.

Objective Function. Let $\mathcal{I}$ denote the set of $(t, g, X, h^{\text{fte}})$ cells, and construct the vector of moment residuals:

$$g(\Omega^S) = \begin{bmatrix} e_1(\Omega^S) \\ e_2(\Omega^S) \\ \vdots \\ e_{|\mathcal{I}|}(\Omega^S) \end{bmatrix}.$$

The supply-side preference parameters are estimated using the Simulated Method of Moments (SMM) criterion:

$$\widehat{\Omega_{est}^S} = \arg\min_{\Omega_{est}^S} \; g(\Omega_{est}^S)^\top W_S \, g(\Omega_{est}^S), \tag{12}$$

where W_S is a positive definite weighting matrix, defaulting to the identity. Each iteration involves solving the dynamic programming problem under cell-specific reservation wages $\widehat{w}_{rw}^{\text{ft}}$ and $\widehat{w}_{rw}^{\text{pt}}$ for all cells, evaluating the moment conditions (11), and updating Ω_{est}^S until convergence is reached.

7.3 Estimation of the Demand Side

Once the supply-side parameters $\Omega^S = \{\phi_t, \gamma, \rho, \beta\}$ have been identified using the stated preference information, the demand-side parameter $\Omega^D = \theta$ is estimated in a second stage. This stage matches labor supply moments from the model to empirical labor market lifecycle profiles displayed in Figure 1. In essence, the second stage answers the question: What level of the part-time wage penalty θ is needed for the model, with preferences fixed from the first stage, to replicate the observed age patterns in labor supply—including the relative prevalence of part-time versus full-time work and the timing of retirement?

Formally, let m^{data} denote a vector of empirical life-cycle moments (e.g., average hours worked, share in part-time employment, and retirement rates), and let $m^{\text{model}}(\theta)$ be the corresponding model-generated moments, conditional on the previously estimated supply-side parameters $\widehat{\Omega^S}$. The demand-side parameter is then estimated using a behavioral SMM criterion:

$$\widehat{\theta} = \arg\min_{\theta} \left(m^{\text{data}} - m^{\text{model}}(\theta)\right)^{\top} W_D \left(m^{\text{data}} - m^{\text{model}}(\theta)\right),$$

where W_D is a positive definite weighting matrix.

The identification of θ relies on comparing behavioral outcomes, which reflect the joint influence of supply and demand, to the stated preference responses, which depend solely on supply-side factors. The gap between the model's predictions based on identified supply-side parameters with no part-time wage penalty and the observed market outcomes pins down the magnitude of θ.

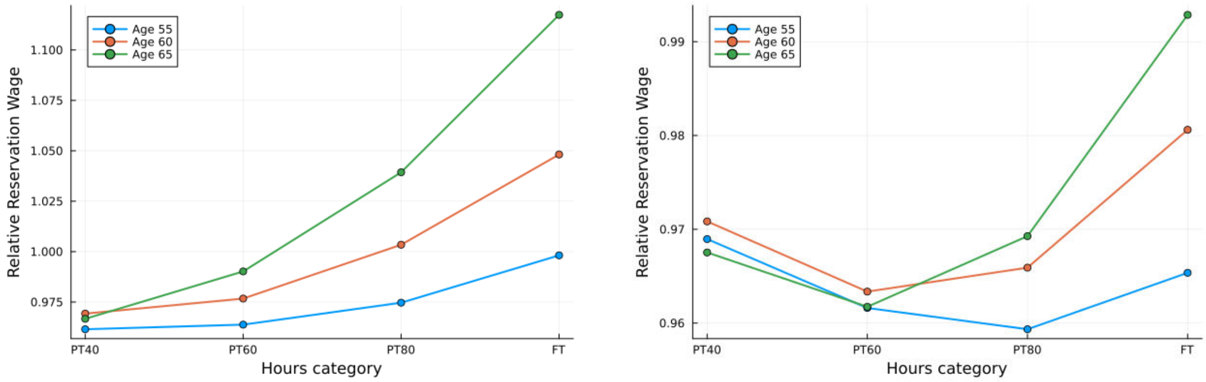
7.4 Results

This section presents the results from the model estimation, as well as preliminary, policy-relevant simulations. While we are currently working on extending the model along several dimensions prior to full-scale structural estimation, it is useful at this stage to illustrate what features are required for the model to generate reservation wage profiles that are consistent with our empirical results.

7.5 Estimation Results

The set of parameters to be estimated are $\Omega_{est} = \{\phi_0, \phi_1, \gamma, \theta\}$. These include both the *supply-side* parameters governing preferences for leisure and the *demand-side* parameters determining the wage schedule across part-time and full-time jobs.

Before finalizing the estimation, it is instructive to illustrate how key parameters interact to produce reservation-wage profiles that align with the empirical patterns observed in our survey data. In particular, the inverse elasticity of substitution for leisure γ plays a central role in shaping the curvature of the reservation-wage schedule across hours categories and ages.



$\gamma = 1.3$ $\qquad\qquad$ $\gamma = 0.8$

Figure 9: Hourly reservation wage schedules across work-hour categories for mid-wealth individuals under two values of the inverse elasticity of substitution for leisure γ (with $\phi_0 = 1.0$, $\phi_1 = 0.1$, and $\theta = 0$.

A higher value of the IES for labor supply, γ, generates a reservation-wage schedule that increases steeply with work hours and rotates upward with age. This is shown on the left-hand side of Figure 9 for $\gamma = 1.3$. This pattern is consistent with the empirical schedule observed for women, who exhibit increasing reservation wages as hours move from part-time to full-time work, in our survey data.

In contrast, for somewhat lower values of the IES for labor supply, the reservation-wage profile becomes U-shaped. This is illustrated for a value of $\gamma = 0.8$ on the right-hand side of Figure 9. Prime-aged individuals demand relatively low reservation wages for full-time work compared to part-time alternatives. However, this pattern reverses later in life, with full-time reservation wages rising sharply. This U-shaped schedule is consistent with the empirical pattern for men, who appear to dislike very low part-time hours throughout the life cycle, while increasingly valuing mid-range part-time work at older ages.

Together, these findings suggest that heterogeneity in leisure preferences across genders—and their evolution with age—is essential for reproducing the observed reservation wage patterns in the data.

8 Conclusions

Distinguishing between supply and demand side factors that shape the labor market behavior of older individuals is notoriously difficult, since observed outcomes reflect both sets of factors. This paper addresses this challenge by fielding a new survey to elicit worker preferences, combining the survey data with observational panel data, and proposing a novel identification strategy to pin down the key preference and technology parameters that govern labor market outcomes. Our survey uses stated preference data from strategic survey questions to elicit workers willingness to pay for various job characteristics, notably reduced hours of work. We use the survey data to generate predicted reservation wages by gender, age and hours worked. We also compute the willingness to pay to reduce weekly hours by 10 as a function of gender, age and hours worked for an individual with average assets and pension points.

We find that prime-aged men typically do not want to work part-time. This is reflected in a negative willingness to pay to reduce hours worked. Unsurprisingly, as men age, their desire to reduce hours worked rises. The reservation wage schedule for 65 year old men is increasing in hours worked. Or put differently, these individuals display a clear willingness to pay to reduce hours worked. For example, the average 65 year old man would be willing to sacrifice roughly 3% of his hourly wage to reduce weekly hours of work from 40 to 30. Intuitively, reservation wages are increasing in age. Conversely, very few women want to work full-time. Their reservation schedules are steeply increasing in hours worked at all ages (above age 50). Similar to men, the reservation wages for women are also increasing in age.

We use the uncovered patterns in reservation wages over gender, age and hours worked to pin down the supply side parameters, namely the intertemporal elasticity of substitution and the disutility of labor supply. Intuitively, we find that a high labor supply elasticity is consistent with the reservation wage patterns we derive for women, while a somewhat smaller elasticity is consistent with the reservation wage patterns for men.

Having identified the demand side parameters, the next step is to pin down the demand side parameters, namely the part-time wage penalty, from our richer life-cycle model. There is much room for related future research, as the fully-fledged quantitative model can be used for policy and welfare analysis.

References

Aaronson, D. and French, E. (2004). The effect of part-time work on wages: Evidence from the social security rules. *Journal of Labor Economics*, 22(2):329–352.

Ameriks, J., Briggs, J., Caplin, A., Lee, M., Shapiro, M. D., and Tonetti, C. (2020). Older americans would work longer if jobs were flexible. *American Economic Journal: Macroeconomics*, 12(1):174–209.

Bacher, A., Grübener, P., and Nord, L. (2025). Joint search over the life cycle. *Journal of Monetary Economics*, 150:103696.

Bick, A., Blandin, A., and Rogerson, R. (2022). Hours and wages*. *The Quarterly Journal of Economics*, 137(3):1901–1962.

Carroll, C. D. (2006). The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economics Letters*, 91(3):312–320.

Chetty, R. (2012). Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply. *Econometrica*, 80(3):969–1018.

Eriksson, T. and Kristensen, N. (2014). Wages or fringes? some evidence on trade-offs and sorting. *Journal of Labor Economics*, 32(4):899–928.

Hudomiet, P., Hurd, M. D., Parker, A. M., and Rohwedder, S. (2021). The effects of job characteristics on retirement. *Journal of pension economics & finance*, 20(3):357–373.

Iskhakov, F., Jørgensen, T. H., Rust, J., and Schjerning, B. (2017). The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks. *Quantitative Economics*, 8(2):317–365.

MaCurdy, T. E. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of political Economy*, 89(6):1059–1085.

Maestas, N., Mullen, K. J., Powell, D., von Wachter, T., and Wenger, J. B. (2023). The value of working conditions in the united states and the implications for the structure of wages. *American Economic Review*, 113(7):2007–47.

Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–3759.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics (P. Zarembka, ed.)*.

Moffitt, R. (1984). The estimation of a joint wage-hours labor supply model. *Journal of Labor Economics*, 2(4):550–566.

Nagler, M., Rincke, J., and Winkler, E. (2023). High-pressure, high-paying jobs? *Review of Economics and Statistics*, pages 1–45.

Nagler, M., Rincke, J., and Winkler, E. (2024). Working from home, commuting, and gender. *Journal of Population Economics*, 37(3):1–23.

Pencavel, J. (1986). Chapter 1 labor supply of men: A survey. In *Handbook of Labor Economics*, volume 1, pages 3–102. Elsevier.

Rogerson, R. and Wallenius, J. (2013). Nonconvexities, retirement, and the elasticity of labor supply. *American Economic Review*, 103(4):1445–1462.

A Proof of Proposition 1

Start from the FOC written in terms of earnings,

$$(1+\theta)\, y_i^{\text{earn}} \left(y_i^{\text{earn}} + a_i\right)^{-\frac{1}{\rho}} = \phi\, h_i^{\frac{1}{\gamma}}, \tag{13}$$

where $y_i^{\text{earn}} = w_i h_i^{1+\theta}$ and ρ and ϕ are common across individuals. Solving for ϕ and taking logs gives

$$\ln\phi = \ln(1+\theta) + \ln y_i^{\text{earn}} - \frac{1}{\rho}\ln\!\left(y_i^{\text{earn}} + a_i\right) - \frac{1}{\gamma}\ln h_i. \tag{14}$$

Define

$$A_i \equiv \ln y_i^{\text{earn}} - \frac{1}{\rho}\ln(y_i^{\text{earn}} + a_i), \qquad B \equiv \ln\phi - \ln(1+\theta),$$

so that (14) becomes

$$\frac{1}{\gamma}\ln h_i = A_i - B. \tag{15}$$

Equation (15) holds for all i. With sufficient cross-sectional variation in $(h_i, y_i^{\text{earn}}, a_i)$, the slope $1/\gamma$ and the composite constant B can be identified. However, since

$$B = \ln\phi - \ln(1+\theta),$$

the data identify only the ratio

$$\frac{\phi}{1+\theta},$$

not ϕ and θ separately. Thus supply-side preferences and the demand-side part-time penalty are not separately identified from market outcomes alone. □

B Taxes

Gross income in period t is defined as the sum of labor earnings, unemployment insurance benefits, and pension income:

$$y_t^{gross} = y_t^{earn} + b_t^{ui} + b_t^{p}. \tag{Gross Income}$$

Individuals contribute to the occupational pension system according to

$$tax_t^{op} = \begin{cases} 0, & \text{if } y_t^{earn} < 9{,}839, \\ 0.0639 \times h_{t-1}^{\text{fte}} \times (y_t^{earn} - 9{,}839), & \text{if } y_t^{earn} \geq 9{,}839, \end{cases} \tag{Occ. Pension Contribution}$$

where h_{t-1}^{fte} denotes the full-time equivalent share of hours worked. The deductible amount is given by

$$Deduct_t = \begin{cases} 0.01753 \times y_t^{earn} - 1,876, & \text{if } y_t^{earn} < 8{,}328, \\ 0.01753 \times 8{,}328 + 0.11213 \times (y_t^{earn} - 8{,}328) - 1,876, & \text{if } 8{,}328 \leq y_t^{earn} < 18{,}147, \\ 0.01753 \times 8{,}328 + 0.11213 \times (18{,}147 - 8{,}328) - 1,876, & \text{if } y_t^{earn} \geq 18{,}147, \end{cases} \tag{Tax Deductible}$$

representing tax-deductible expenses that depend on earned income.

The health insurance contribution is defined as

$$tax_t^{med} = \begin{cases} 0.0125 \times y_t^{gross} + 399, & \text{if } y_t^{gross} < 30{,}320, \\ 0.0125 \times 30{,}320 + 399, & \text{if } 30{,}320 \leq y_t^{gross} < 33{,}514, \\ 0, & \text{if } y_t^{gross} \geq 33{,}514, \end{cases} \tag{Health Insurance Contribution}$$

and the unemployment insurance contribution is

$$tax_t^{ui} = \begin{cases} 0, & \text{if } y_t^{gross} < 15{,}562, \\ 0.058 \times (y_t^{gross} - 15{,}562), & \text{if } 15{,}562 \leq y_t^{gross} < 44{,}800, \\ 0.058 \times (44{,}800 - 15{,}562), & \text{if } y_t^{gross} \geq 44{,}800. \end{cases} \tag{UI Contribution}$$

Taxable income is then given by

$$y_t^{taxable} = \max\{0, y_t^{gross} - tax_t^{ui} - tax_t^{med}\}. \tag{Taxable Income}$$

Social security contributions depend on whether the individual has reached the state pension age:

$$tax_t^{soc} = \begin{cases} 0.324 \times y_t^{taxable}, & y_t^{taxable} < 30{,}371 \text{ and before pension age,} \\ 0.324 \times 30{,}371, & y_t^{taxable} \geq 30{,}371 \text{ and before pension age,} \\ 0.145 \times y_t^{taxable}, & y_t^{taxable} < 30{,}371 \text{ and after pension age,} \\ 0.145 \times 30{,}371, & y_t^{taxable} \geq 30{,}371 \text{ and after pension age.} \end{cases} \tag{Social Security Tax}$$

Income tax before deductions follows a progressive schedule with four brackets:

$$tax_t^{incpre} = \begin{cases} 0.01 \times y_t^{taxable}, \\ 0.01 \times 16{,}721 + 0.0795 \times (y_t^{taxable} - 16{,}721), \\ 0.01 \times 16{,}721 + 0.0795 \times (30{,}371 - 16{,}721) + 0.42 \times (y_t^{taxable} - 30{,}371), \\ 0.01 \times 16{,}721 + 0.0795 \times (30{,}371 - 16{,}721) + 0.42 \times (52{,}072 - 30{,}371) + 0.52 \times (y_t^{taxable} \end{cases} \tag{Income Tax Pre Deductions}$$

After accounting for deductions and a fixed allowance of 1,876, the post-deduction income tax is

$$tax_t^{inc} = tax_t^{incpre} - Deduct_t. \tag{Income Tax Post Deductions}$$

Finally, total taxes are the sum of all applicable components:

$$Tax_t^{total} = tax_t^{ui} \cdot \mathbb{I}\{op_t = 0\} + tax_t^{med} + tax_t^{soc} + tax_t^{inc} + tax_t^{op}. \tag{Total Taxes}$$

C Evaluation of Expectations

In appendix, we briefly illustrate how we evaluate expectations. Recall that the first-order condition for optimal consumption

$$c_t^{-\frac{1}{\rho}} = \beta \cdot \psi_t \cdot R \cdot \mathbb{E}_t^{\lambda^\varepsilon} \left[c_{t+1}^{-\frac{1}{\rho}} \right],$$

which requires evaluating expectations over future choices and values is essential. Thus, we here introduce some concepts that are helpful in this endeavor. Note first that taste shocks are uncorrelated. Therefore, we can rewrite the continuation value of the worker as

$$\mathbb{E}_t^{\lambda^\varepsilon}\left[V_{t+1}\left(m_{t+1}, pr_{t+1}|\Omega^D, \Omega^S\right)\right] = EV_{t+1}^{\lambda^\varepsilon}\left(m_{t+1}, pr_{t+1}, d_{t+1}\right)$$

For the taste shock, we use the well-known log-sum formula for independent, extreme-value distributed random variables. The integral over y then accounts for expectations over the income shock, can be evaluated using standard methods and discritization of y. For the taste shock, we use the well-known log-sum formula for independent, extreme-value distributed random variables

$$\begin{aligned} EV_{t+1}^{\lambda^\varepsilon}\left(m_{t+1}, pr, d_{t+1}\right) &= \mathbb{E}_t\left[\max_{d_{t+1}\in\mathcal{D}}\left\{v_t\left(m_{t+1}, pr_{t+1}, d_{t+1}\right) + \lambda\epsilon\left(d_{t+1}\right)\right\}\right]. \\ &= \lambda^\varepsilon \cdot log\left(\sum_{d_{t+1}\in\mathcal{D}}\exp\left(\frac{v_t\left(m_{t+1}, pr_{t+1}, d_{t+1}\right)}{\lambda^\varepsilon}\right)\right) \end{aligned}$$

We apply similar techniques to compute expectations over the policy function when evaluating the Euler equation.

D More details

The first order condition

The Euler equation for optimal consumption is derived as follows:

$$c_t^{-\frac{1}{\rho}} = \beta \cdot \psi_t \cdot R \cdot \mathbb{E}_t^{\lambda^\varepsilon}\left[c_{t+1}^{-\frac{1}{\rho}}\right]$$

which can be rewritten as

$$\begin{aligned} \left[c_t\left(m_t, pr_t, d_t\right)\right]^{-\frac{1}{\rho}} &= \beta \cdot \psi_t \cdot R \cdot \sum_{d_{t+1}\in\mathcal{D}} P_{t+1}\left(d_{t+1}|m_{t+1}, pr_{t+1}\right) \cdot \left[c_{t+1}\left(m_{t+1}, pr_{t+1} d_{t+1}\right)\right]^{-\frac{1}{\rho}} \\ c_t\left(m_t, pr_t, d_t\right) &= \left(\beta \cdot \psi_t \cdot R \cdot \sum_{d_{t+1}\in\mathcal{D}} P_{t+1}\left(d_{t+1}|m_{t+1}, pr_{t+1}\right) \cdot \left[c_{t+1}\left(m_{t+1}, pr_{t+1} d_{t+1}\right)\right]^{-\frac{1}{\rho}}\right)^{-\rho} \end{aligned}$$

where $P_{t+1}\left(d_{t+1}|m_{t+1}, pr_{t+1}\right)$ the logit choice probabilities that arise due to the distributional assumption for the taste shocks and are given by

$$P_{t+1}\left(d_{t+1}|m_{t+1}, pr_{t+1}\right) = \frac{\exp\left(\frac{v_{t+1}\left(m_{t+1}, pr_{t+1}, d_{t+1}\right)}{\lambda^\varepsilon}\right)}{\sum_{d''_{t+1}\in\mathcal{D}}\exp\left(\frac{v_{t+1}\left(m_{t+1}, pr_{t+1}, d'_{t+1}\right)}{\lambda^\varepsilon}\right)}.$$

E Construction of Data moments

E.1 1st Stage data

From our survey we have data for 2,365 individuals reporting reservation wages for their reference job (which can be a full-time, or a part-time job) and a strategic survey question (SSQ) about the respective hours which the respondent did not have in his/her refernce job. We define the scenario age as the age at which the respondent is supposed to make the decision asked in the SSQ. For current workers this is the current year, while for people who worked in the past (e.g. retirees) this is the time right before their reference job ended. Given that we did not ask the respondent about all the state variables assumed in our structural model, we need to merge our survey with the core LISS panel data to get informatoin on net assets and the stock of pension rights. In the following we describe how we construct these data.

Asset Data

We use data from 'Assets-LISS Core Study' which we have information from 2008-2024 for every other year (i.e. 9 waves). Asset info is asked for 31.12.YEAR-1. We treat it as beginning of period t assets, i.e. we assume that 31.12.2023 assets are the beginning of 2024 asset values. We write the model accordingly and it allows us to have 2024 asset values for our survey respondents.

We define household net assets as the sum of bank accounts, stocks/bonds/funds, other real estate note of mortgage for this, durable goods (car etc.), money loaned out, miscellaneous assets, equity in businesses etc., minus student loans, other debt and adding the value of the primary residence (if owned) minus its mortgage.

Given that the scenario age is in the past for many respondents and due to missing observations, we only have information on asset holdings at scenario age for around 28% of our survey respondents (667/2365). For this reason we need to impute values and proceed as follows:

First, for each individual with missing observations on interior gaps or missings at the boundaries (e.g. for the years where assets are not recorded), we linearly inter- and extrapolate asset values using the neighboring entries. This yields an additional 270 observations (11% of the sample).

Second, we estimate a random effects model using the original (non-imputed) assets on a set of co-variates from the background variable file in LISS (age, current employment status, gender, position in household, age of household head, number persons living in household, number of kids, partnered, marital status, owner/renter, region, 2nd order polynomial in gross income (2024 value for workers taken from our survey), education, and year. All variables are treated as dummies except the income variable. We predict the assets for another 978 observations (41% of the sample).

With this procedure, we end up with net assets for 81% of the sample (1,915 out of 2,365). The quality of our imputations are reasonable. The correlation between the true assets and the interpolated ones is 0.94, and the correlation with the imputations for the random effects model is 0.54. The remaining missing values often come from retirees (only 60% asset coverage) who retired before they entered the LISS survey.

Income Data

We directly asked questions about gross annual income of the reference job at scenario age. For respondents who never worked at an employer, we construct a 'hypothetical' job where we used estimated annual income which was predicted based on several respondent characteristics (age, gender, employment status, etc.).

Pension entitlements

In the LISS we have information about the projected gross pension benefit per year from old age pension age onward. This information is relatively easy to obtain in the Netherlands through the official digital platform *Mijnpensioenoverzicht.nl*, which consolidates data from all registered pension providers. Access to this platform requires authentication via DigiD, the national digital identification system. Once logged in, users receive a comprehensive overview of their accumulated rights from various employment periods and pension funds, including projections of their total pension income at the statutory retirement age. The information is standardized across all providers, ensuring comparability and clarity. This infrastructure makes it relatively easy for citizens to gather this information for the survey.

For the pension entitlements, we only need information for current workers, as well as for retirees with a scenario age in the past. We again impute in an analoguous way and end up with 561 truely observed pension entitlements, 203 interpolated values (corr with true value is 0.2) and 1024 predicted values (corr with true value is 0.4).

F Additional Results of the Survey

F.1 Censoring

Table A1: Distribution of Reservation Wage Categories, Full Sample

Category	Frequency	Percent
RW <= 2	3353	76.0
2 < RW <=10	60	1.4
Never Acc.: slider at 0 (prop. not moved)	945	21.4
Never Acc.: slider moved to >0	49	1.1
Never Acc.: slider moved to the end	5	0.1
Total	4412	100.0

Table A2: Distribution of Reservation Wage Categories, Restricted Sample (Part-time)

Category	Frequency	Percent
RW <= 2	1382	85.0
2 < RW <=10	20	1.2
Never Acc.: slider at 0 (prop. not moved)	209	12.9
Never Acc.: slider moved to >0	15	0.9
Total	1626	100.0

F.2 Descriptive Statistics

Table A3: Summary Statistics: Full vs. Restricted Sample

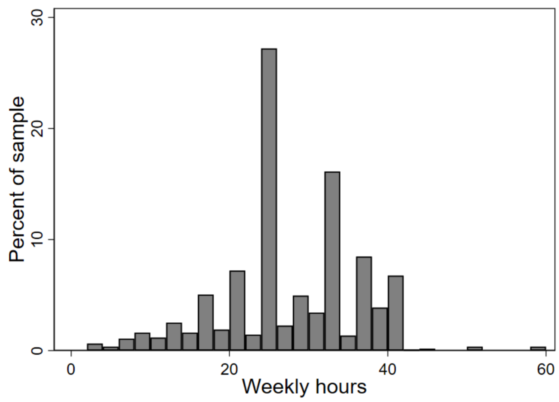
	Full sample		Restricted sample	
	Mean	SD	Mean	SD
Retired	0.34	0.47	0.23	0.42
Employed	0.46	0.50	0.62	0.49
Non-workers	0.04	0.20	0.03	0.18
Age 45-49	0.10	0.31	0.13	0.33
Age 50-54	0.12	0.33	0.15	0.36
Age 55-59	0.16	0.36	0.19	0.39
Age 60-64	0.19	0.39	0.22	0.41
Age 65-69	0.19	0.39	0.17	0.37
Age 70-75	0.24	0.43	0.15	0.36
Female	0.50	0.50	0.49	0.50
Have Partner	0.72	0.45	0.74	0.44
number of kids in hh	0.54	0.97	0.64	1.01
Low Education	0.23	0.42	0.20	0.40
Medium Education	0.37	0.48	0.37	0.48
High Education	0.40	0.49	0.43	0.49
Observations	2200		1622	

Notes: The restricted sample includes only respondents for whom net assets and pension entitlements are observed at the scenario date.

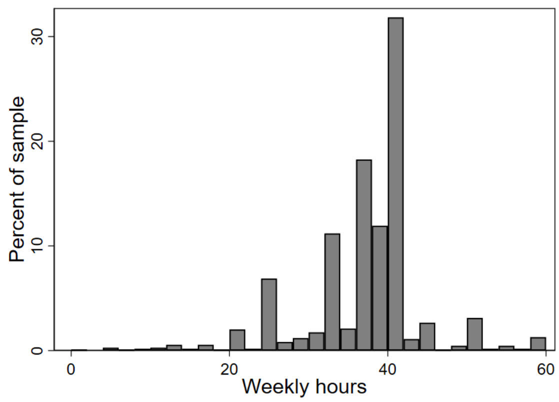
Table A4: Job Characteristics of Reference Jobs

	Retired	Employed	Non-worker
Scenario Age	62.86	55.89	55.54
Tenure in RJ	27.76	17.34	10.45
Annual gross income	48162.93	48801.84	43264.13
Wage per hour in RJ	28.31	28.45	27.81
Hours worked per week	32.65	32.35	29.57
Fulltime (yes/no)	0.53	0.49	0.30
Inflexible Job (yes/no)	0.35	0.31	0.09
Stress (yes/no)	0.44	0.41	0.41
Physical (yes/no)	0.37	0.41	0.52
Observations	375	1003	54

Figure A1: Distribution of Weekly Reference-Job Hours by Gender



(a) Women



(b) Men

Notes: Hours refer to the respondent's reference job. Hours above 60 are winsorized at 60.