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The value of commuting time, flexibility, and job security: Evidence from current and recent jobseekers in Flanders[☆]

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ABSTRACT

This study examines jobseekers' preferences for a variety of job attributes. It is based on a choice experiment involving 1852 clients of the Flemish Public Employment Service (PES). Respondents value flexibility (e.g., remote work and schedule flexibility), job security and social impact of the job, and require significant compensation for longer commute times. A majority (70%) would need very substantial wage increase beyond their acceptable baseline wage to compensate for less flexibility, job security or social impact. These findings enhance our understanding of labour supply decisions and can inform the design of salary packages and HR policies.

1. Introduction

Understanding the preferences and priorities of jobseekers is essential for designing effective labour market policies and for employers seeking to attract and retain talent. Much research has been focused on monetary compensation and studied the role of reservation wages, but neglected the value jobseekers place on other job attributes, although it is widely accepted among economists that the "wage" as a central concept in labour market theories should be interpreted as a multidimensional index that does not only capture monetary wages but also the value of all job amenities and disamenities (see Eriksson and Kristensen, 2014).[1]

The monetary compensation needed to make people indifferent between jobs with different non-monetary amenities will depend on the workers' preferences and circumstances. The empirical literature has used various strategies to identify such compensating differentials. For example, Sorkin (2018) analyses employer-to-employer transitions of workers in the US to estimate employees' ranking of firms and to estimate compensating differentials necessary to move between firms with a different rank. While existing studies have shed light on the impact of various sociodemographic characteristics and institutional factors, such as gender (Brown et al., 2011), perceived and actual

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[1] The importance of the multidimensionality of a remuneration package is underpinned by the theory of compensating differentials, which implies that workers may be indifferent between jobs offering different wages as long as the wage differential reflects the value of other job (dis)amenities.

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macroeconomic conditions and unemployment duration (Brown and Taylor, 2015; Krueger and Mueller, 2016), as well as the generosity of the benefit system (Le Barbanchon et al., 2019) on the monetary value of the reservation wages, only recently attention has been paid to the sensitivity of reservation wages to changes in non-monetary job characteristics.[2] Several of these studies (see, e.g., Felfe, 2012; Mas and Pallais, 2017; Dupuy et al., 2021; Sockin, 2021; Maestas et al., 2023) consider a broader set of job characteristics beyond monetary remuneration and find that individuals are willing to exchange wage for favourable job characteristics. As a consequence, it seems more appropriate to consider *reservation jobs*, rather than solely focusing on *reservation wages*. When reservation wages are elicited in surveys, often by asking respondents to state their reservation wage, it is typically not controlled for what other job amenities respondents have in mind when expressing their reservation wage.[3]

In this paper, we contribute to filling this gap in the literature. We investigate how jobseekers weigh various job characteristics against each other to assess how jobseekers rank bundles of job characteristics and examine to what extent such valuations are heterogeneous across groups of individuals. We focus in particular on the role of flexibility, specifically scheduling flexibility and the ability to work from home (WFH), but also consider commuting time, which is not a job attribute, strictly speaking, yet has been shown to significantly influence job acceptability and job search behaviour (van den Berg and Gorter, 1997; van Ommeren et al., 1999; Manning, 2003; Le Barbanchon et al., 2021). This allows for a better understanding of reservation jobs in today's labour market where working from home becomes possible for an increasing number of jobs due to digitalisation and technological progress.

To this end, we use a discrete choice experiment (DCE) methodology, which is particularly well-suited for analysing multidimensional decision-making processes, as DCEs allow for the differentiation of several aspects by including multiple attributes. By exogenously varying these attributes, it becomes feasible to measure the relative importance of the attributes on a single behavioural outcome variable, such as job choice. Unlike earlier studies, we explicitly take into account that some jobs cannot be performed from home. We use different experimental designs depending on the feasibility of working from home.

The focus on flexibility is timely as digitalisation and technological progress make working from home possible for an increasing number of jobs, and because the COVID-19 pandemic prompted a shift towards remote work arrangements.[4] Working from home increases flexibility and potentially reduces costs, due to less commuting, aligning with the growing importance of sustainability considerations.[5] This development raises the question of whether jobseekers are already taking these considerations into account and are prepared to accept jobs that offer lower wages but higher schedule flexibility or reduced commuting time.

Our analysis employs conditional logit models to estimate jobseekers' preferences for job attributes based on their choices in the DCE. We find that on average all characteristics are valued and that estimates of willingness to pay (WTP) or willingness to accept (WTA) for changes in all of the characteristics are statistically significant and economically meaningful. Latent class analysis reveals that there is substantive heterogeneity across people. For a large minority of 30%, the wage plays a very important role in the decision-making process, and these respondents require relatively moderate compensations for less favourable job conditions. For example, an increase in the daily commuting time by 15 min could be compensated for with a net pay increase of 6%. Having complete working from home flexibility versus having no possibility at all would be equivalent to a wage increase of just over 7%. For a majority of 70%, the non-monetary characteristics have a much higher weighting. In fact, once these respondents receive a certain baseline wage, substantial compensations are needed when certain job characteristics become less favourable. For example, this group would need a wage increase of 20% in order for them to accept an increase in the daily commuting time by 15 min. This group would also forego any proposed wage increase beyond their baseline wage (more than 50%) if they could instead have more social impact. The other attributes only have a slightly lower valuation. While the grouping in the latent class procedure is data driven, observable characteristics such as being older are positively associated with the chance of belonging to the class with stronger preferences for the non-monetary attributes. These results provide insights into the relative importance of different job attributes and highlight variations in preferences across groups.

Our research contributes to the literature in several ways. Firstly, our study complements the literature on compensating differentials, of which a very recent and growing branch is based on choice experiments or contingent valuation to elicit preferences, with new empirical evidence from recent jobseekers. Studies in the post-pandemic context have tried to gain insights through online convenience panels, which are becoming popular in economics and offer a convenient way to obtain survey data from a guaranteed number of individuals. Respondents of such convenience studies are typically drawn from a pool of potential respondents who have registered with the respective survey company and are compensated for each survey they complete. In this study, however, we collaborated with the *Vlaamse Dienst voor Arbeidsbemiddeling en Beroepsopleiding* (VDAB), a Public Employment Service (PES) in Flanders (Belgium) to approach their clients who were either current or very recent jobseekers. Many of them have not been in stable employment relationships for years and all of them have been recently engaged in the job search process. Not only might PES clients have thought more thoroughly about the different dimensions than a general sample of the population, but they are also of particular relevance for policymakers and firms as they are among those who are moving to a new equilibrium.

Secondly, and related to the previous point, the collaboration with VDAB allows us to merge survey data with administrative data which is not restricted to those clients who have responded to the survey. Our inclusion of administrative data allows for an exploration of non-response

[2] Another set of studies has evaluated policies designed to affect the supply side by affecting the reservation wage, or that target the demand side by offering employers incentives to match reservation wages of jobseekers. Examples include the effect of unemployment benefits on the job finding rate or post-unemployment job quality (Lalive, 2007; Johnston and Mas, 2018), the generosity of disability benefits or childcare subsidies on the employment rate of disabled individuals and parents, respectively (Bettendorf et al., 2015; Lefebvre et al., 2009; Maestas et al., 2013), and the impact of wage subsidies on the employment prospects of target groups (Boockmann et al., 2012).

[3] Additionally, measurement problems arise in practical applications, e.g., when asking jobseekers to state their (monetary) reservation wage in surveys. For example, a recent literature shows that people are often too optimistic about their labour market prospects leading to a higher reservation wage than would be the case under unbiased beliefs, which can imply longer unemployment spells and a necessary downward revision over time (Caliendo et al., 2023; Mueller et al., 2021; Jäger et al., 2024).

[4] Using data from before and after the outbreak of the pandemic, Bick et al. (2023) document a sharp increase in WFH and their evidence suggests that these increases might not only be due to health risks and could be a more permanent shift in working conditions, a hypothesis supported with data from the US and beyond (Aksoy et al., 2022; Hu et al., 2021).

[5] Recent studies have assessed the willingness to pay for job characteristics during and after the pandemic using contingent valuation methods or choice experiments implemented in online panels (Aksoy et al., 2022; Nagler et al., 2022). Estimates of compensating differentials for having the possibility of working from home are in the range of 5 to 10% of the current wage, and there is variability across countries, socio-demographic characteristics such as gender and dependent children, and commuting time.

patterns and their potential implications for estimates of compensating differentials. Finally, our dynamic survey design tailors job choices to respondents' real-world situations. While such a strategy is believed to increase the quality of responses (Maestas et al., 2023), in our case it also allows us to study asymmetries in the shadow price of commuting time below and above an individual-specific baseline or reference point and to better capture preference heterogeneity across groups of people. Through these contributions, our study offers valuable insights into the multidimensional nature of job preferences and their implications for labour market outcomes.

The remainder of the paper is structured as follows. Section 2 describes research that relates to the job characteristics we focus on. Section 3 provides an overview of the data collection process, the survey content and the choice experiment design, and offers descriptive statistics of the baseline job characteristics used in our choice experiments. Section 4 presents the findings from the Flemish PES sample. Finally, Section 5 offers some concluding remarks.

2. Related literature

There is a substantive literature in labour economics that attempts to estimate compensating differentials using various methods. More recently, choice experiments have become increasingly common for this purpose. In Appendix Table A.1, we summarise papers that use choice experiments similar to ours. We have only included studies in the table that examine attributes overlapping with those in our paper. As such, studies focusing on other job characteristics such as workplace happiness (Ward, 2022) or shift work (Desiere and Walter, 2023) are not included nor discussed.

As can be seen from the table, schedule flexibility — not to be confused with the flexibility to decide on hours worked — has most often been included in other experiments, and often schedule flexibility and the possibility of working from home, are studied simultaneously. Mas and Pallais (2017) ask applicants during a recruitment process for call centre operators to make a trade-off between a job with a higher wage and a job with more options to work from home or with schedule flexibility. While they find that most workers are not willing to pay for schedule flexibility, the few that are, are willing to sacrifice a significant proportion of their wage. They find that the average worker is willing to give up 20% of wages to avoid a schedule set by an employer on short notice and willing to give up 8% for the option to work from home. While WTP cannot be compared across studies, as attributes are not standardised, Ghorpade et al. (2023), Jost and Möser (2023), Lewandowski et al. (2023), Maestas et al. (2023), Nagler et al. (2022), and Eriksson and Kristensen (2014) all find that some degree of (schedule and/or time) flexibility is positively valued. The valuation differs somewhat depending on contractual working hours and employment type. Moreover, large differences across workers and jobseekers are found. Only Lanfranchi et al. (2010) find that for nonprofit workers, the transition from the baseline schedule (working time decided by the employer) to rotating shifts results in a negative WTP.

Maestas et al. (2023) use data from choice experiments conducted with American workers to gauge the willingness to pay for a wide and comprehensive range of job attributes. Besides working from home and schedule flexibility, they also analyse the role of a meaningful job and find that frequent opportunities to impact the community/society are worth an additional 3.6% of the wage relative to occasional opportunities. Similarly Non et al. (2022) find that science and engineering students value jobs at high-tech companies that focus on corporate social responsibility (CSR) and sustainability much more than similar jobs offered by other high-tech companies (focusing on profits or, to a lesser extent, on innovation). Graduates are willing to give up 220 euros net pay per month to work in a company that promotes CSR and sustainability. Non et al. (2022) also analyse the role of job security in students' job choices, specifically the choice between jobs with temporary and permanent contracts. They add a layer for temporary contracts in which they distinguish between jobs with high or low chances of receiving a permanent contract afterwards. Wiswall and Zafar (2018) also focus on students, but distinguish between jobs based on the likelihood of being fired. Both studies find that students value job security highly, while also acknowledging heterogeneous results e.g. with respect to risk preference (Non et al., 2022) and gender (Wiswall and Zafar, 2018).

To the best of our knowledge, there are only two DCEs including daily commuting time. Nagler et al. (2022) find, using a German convenience sample from the working population, that workers' WTP for reducing their commuting time from 45 to 15 min amounts to 13.2% of earnings. Feld et al. (2022) confirm the high valuation of commuting time for Egyptian jobseekers and document that the compensation that women require for a longer commute is twice as high as that of men.

There are additional studies investigating attributes similar to those in our paper, but which employ different methodologies. For example, some studies use settings where individuals are asked to state their reservation wage or threshold for other amenities, rather than choosing between different jobs. Le Barbanchon et al. (2021) use administrative data on French jobseekers, who are required to state their reservation wage and maximum commuting time or distance, and they estimate that the compensating differential for commuting time is around 20% higher for women compared to men. He et al. (2021) posted online job ads that vary in terms of time and location flexibility and find that jobseekers value flexibility in time as well as in location. Jobs that offer flexibility in both dimensions are even valued more than jobs that only offer flexibility in one dimension.

In a field experiment, Kesternich et al. (2021) offers a pool of employed and unemployed people a one-hour job that can be done from home. There are two types of job descriptions that are randomly assigned to the participants: the low-impact job involves digitising documents for archiving purposes but that will not be used again in the future. The high-impact job involves digitising documents for medical research. Individuals are then asked to state a reservation wage. If this stated reservation wage is lower than the threshold randomly drawn by a computer, they will be assigned the job. It turns out that, on average, the reservation wage is not much affected by whether the job is meaningful or not, but this average masks substantial heterogeneity. For example, employed individuals state a lower reservation wage if the job is meaningful, while the opposite is true for unemployed people. Those who in the survey state that the meaningfulness for a job is important for them, state the reservation wage that is almost 18% lower in the high-impact treatment than in the low-impact treatment.

Other studies use quasi-experiments. For example, Mulalic et al. (2014) exploits the relocation of firms as a quasi-natural experiment to estimate the compensating differential for commuting time, and establishes a positive elasticity of wage with respect to commuting distance.

While recent studies consider a broader set of job characteristics beyond monetary remuneration, we add the specific angle of considering the interdependency of working time flexibility, working from home and commuting time simultaneously, and this in a post-Covid-19 era for a sample of individuals who have been recently engaged in job search.

3. Research design

3.1. Experimental design

3.1.1. Discrete choice experiment (DCE)

At the core of this study is a DCE designed to assess the willingness of (recent) jobseekers to pay for specific job attributes. DCEs have been used for analysing multidimensional decision-making processes in fields such as marketing, health and environmental economics, and are rapidly gaining popularity in other sub-disciplines such as labour economics. By exogenously varying the alternative attributes (job characteristics in our case), it becomes feasible to measure the relative importance of the attributes on one single behavioural outcome variable (job choice in our case).

Stated preferences methods such as choice experiments offer a lot of flexibility compared to revealed preferences methods: the latter are based on actual choices agents make in real life and opportunities to conduct ceteris paribus analyses in a real-world setting are scant. Furthermore, studies such as Hainmueller et al. (2015) and Maestas et al. (2023) offer evidence in support of the external validity of choice experiments.

We designed a *dynamic* DCE tailored for jobseekers in which we build on respondents' initial survey responses. This dynamic character offers several unique features. First, the survey responses guide individuals into two distinct design pathways, labelled Design 1 and Design 2. Respondents were assigned to Design 1 if they, at the time of survey participation, were either working or desiring to work in a job that can be done from home (N=589).[6] Conversely, Design 2 was assigned to respondents engaged in or aspiring to a job that is inherently unsuitable for remote work (N=1154). Second, we anchor the levels of several attributes, such as wage, on responses provided earlier on in the survey. For example, we asked for the lowest wage that would make a job acceptable for the respondent, and only displayed jobs in our DCE that had a higher wage than this stated reservation wage, but would also not exceed it by more than 50%.[7] Third, we impose monotonicity assumptions on utility derived from certain attributes, such as wage and commuting time. These assumptions, combined with the dynamic character of the DCE, ensure meaningful choices that engage respondents without causing distress or confusion.

The essence of the DCE involves selecting between two hypothetical jobs within six distinct choice sets. Respondents are tasked with choosing between two jobs that differ in wage and in *one additional dimension*.[8] In line with standard practice for choice experiments, we employ a colour-coded scheme to highlight the distinguishing features of the two jobs. This visual aid aims to help respondents focus on the pertinent information, streamlining their decision-making process. Each choice task prompts respondents to indicate their preferred job and the strength of their preference. Each choice task is presented on a separate screen. An illustrative example of a choice task from Design 1 is depicted in Fig. 1.

Jobs are described by five or six attributes, depending on whether or not one has or aspires to a WFH-feasible job. Design 1 included 120 potential choice tasks, each contrasting two distinct jobs, while Design 2 contained 60 choice tasks. The levels of the job attributes in the choice tasks are determined using a D-optimality algorithm (Hole, 2015), which maximises the precision of the coefficient estimates in the econometric model subject to the constraint that only the wage and one additional characteristic differ between the two jobs. The jobs presented in each choice task are mutually exclusive and collectively exhaustive. To prevent one alternative from dominating the other, we ensured that no job was more attractive on all dimensions. Additionally, to avoid instances where neither job met the jobseeker's criteria, we recoded ties at the least attractive attribute levels to either the intermediate or most attractive levels in equal proportions within such choice tasks.

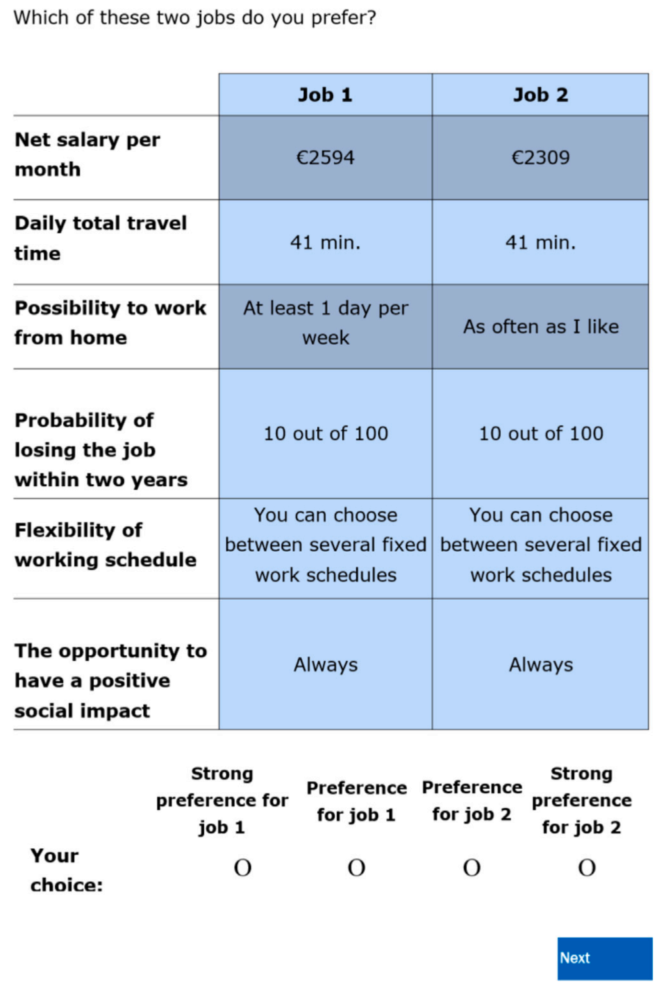

Fig. 1. Screenshot of an example of a choice task: Design 1.

3.1.2. Choice of attributes and levels

Jobs vary across five or six attributes: wage, commuting time, working from home (only included in Design 1), schedule flexibility, job security and impact on society.[9] The latter two, while arguably being less topical in light of the post-pandemic context, are included to benchmark our results. Table 1 provides an overview of the job attributes and their corresponding levels.

By including schedule flexibility, working from home and commuting time simultaneously, we explicitly take into account the interdependency of these job amenities allowing flexibility in work. This is especially relevant given today's labour market that, due to digitalisation and technological progress as well as the COVID-19 pandemic, allows working from home for an increasing number of jobs. It has been argued that working from home can save about $4000 per year.[10] Besides the direct costs related to commuting, the literature has documented negative effects of commuting on life satisfaction and various measures of mental and physical health (see, e.g., Botha et al., 2023; Roberts et al., 2011; Jacob et al., 2019; Stutzer and Frey, 2008; Künn-Nelen, 2016). Due to the setup of the discrete choice experiment, we can analyse whether (recent) jobseekers are willing to accept lower

[6] We will refer to such jobs as WFH-feasible.

[7] For ethical reasons, we did not display a choice menu in which the jobs fell below the stated reservation wage. In the introduction of the survey, it was made clear that participation was completely voluntary and anonymous, and that answers or participation would not affect the trajectory with the Public Employment Service (PES). However, PES clients remain a potentially vulnerable group. To reduce the chance that the survey would cause distress or confront jobseekers with inappropriately low wages, one of the measures was not to offer wages below their current net wage or their stated monetary reservation wage.

[8] While statistical efficiency favours choice tasks with alternatives differing on multiple dimensions, research suggests that respondents may struggle with such tasks (Flynn et al., 2016). To address this, we limit the number of attributes that differ within each choice task.

[9] The significance of societal impact has gained increasing attention in recent literature (see,e.g., Cassar, 2018; Kesternich et al., 2021; Non et al., 2022).

[10] See https://www.flexjobs.com/blog/post/benefits-of-remote-work.

Table 1
Overview of job attributes and their levels in the discrete choice experiment.

Attributes	Levels
Wage	Between 1 and 1.5 times the reported (reservation or actual) wage
Commuting time	Reported commuting time minus 15 min
	Reported commuting time
	Reported commuting time plus 15 min
Working from home[a]	Never
	At least one day per week
	At least two days a week
	As much as I want
Schedule flexibility	You have no say in your schedule
	You can choose from different fixed schedules
	You can at all times ask permission to change your schedule
	You can determine your schedule yourself
Likelihood of losing job	One out of hundred
	10 out of hundred
	20 out of hundred
Impact on society	Rarely
	Sometimes
	Often

[a] Only applicable in Design 1, i.e., for individuals that report a job that can be done from home (based on (Dingel and Neiman, 2020).
Notes: If respondents report a (desired or actual) commuting below 15 min, this value is adjusted to 15 min for calculating the commuting time displayed in the choice experiments. To accommodate workers who only work one or two days per week, we tailored versions of Design 1 by aligning the maximum WFH days with their work schedule. These customised versions were specific to five respondents, and we therefore excluded those respondents from the analyses. The likelihood of job loss within the next two years is henceforth referred to as "Job Security".

wages in exchange for less commuting via either a shorter commute and/or working from home.

Wages and commuting times are determined based on answers to earlier survey questions to ensure the realism of the choice tasks. Anchoring the wage of the jobs in the choice tasks to the reservation wage indicated by respondents in the initial survey guarantees that none of the displayed jobs fall below the minimum requirement in the relevant job dimension. Referencing to respondents' willingness to commute daily as stated in the initial survey, we set commuting time levels such that the maximum difference in commuting time between two jobs in a choice task is 30 min, approximately equivalent to the commuting time between two commuting zones in Flanders. This approach tailors the daily commuting time to align with individual preferences and reflect the Flemish context accurately. The inclusion of Working from home is contingent on respondents foreseeing that their current or desired job allows for remote work.

3.2. Data and estimation sample

We collected data among the full population of clients of the Flemish PES who became eligible for claiming unemployment insurance (UI) benefits in January or February 2021, along with all final-year students who had voluntarily registered in the system by 30 June 2021 and were searching for a job, totalling about 38,000 individuals, whom we define as *invitees*.[11] The survey was launched on July 7, 2021, with reminders sent on July 14, 29, and August 2, and was closed on August 9, 2021.

Not all *invitees* responded to the sample so that we are left with a sub-sample of *respondents* (N = 1852) and *non-respondents* (N = 36,225). Since individuals were invited in July, some of the *invitees* had already found a job when responding to the survey. We refer to this subsample of *respondents* as the *recent jobseekers* (N =1048), while we refer to the group of people who are still unemployed or who have re-entered unemployment and are looking for a job as the *current jobseekers* (N =804). The 1852 respondents can furthermore be divided into a sub-sample of *reliable* respondents (N=1743) and less reliable respondents (N=109), as explained below.

In order to investigate how *invitees* differ from individuals who entered unemployment at a different date in 2021, we retrieved administrative data for the group of individuals registered with VDAB in the period from March to December (and who had not registered with VDAB in the first two months of the year), and refer to them as the sample of *non-invitees* (n =127,079). A schematic overview of the samples is given in Table 2.

3.3. Survey design

The survey comprises two main sections. The first section focuses on introductory questions and queries about desired (current jobseekers) or current employment (recent jobseekers). The second section presents the choice experiment where respondents are asked to make six choices between two hypothetical job scenarios. As previously mentioned, these scenarios are tailored to each respondent's circumstances, by leveraging information from the first section of the survey, to ensure that respondents are presented with job choices that resonate with their situation.

The first section includes questions about working hours and days, remuneration and the desired (or actual) number of working hours, preferred (or actual) weekly workdays, and the net wage respondents are earning or want to earn as a minimum. Recent jobseekers, i.e. those who were already employed at the time of the survey, may be hesitant to disclose their current wages, however. To address this concern, we offered them an alternative if they left the wage field blank: they would first receive a prompt indicating that the field was incomplete. Subsequently, if they proceeded without inputting a value, they would then be presented with wage categories to choose from. This approach aimed to minimise the reliance on wage category data. The lowest category (500 EUR/month or less) was assigned an anchoring value of 500, while the highest category (more than 5000 EUR/month) received an anchoring value of 7500. All intermediate categories (e.g., 501–1000 EUR/month) have a width of 500 EUR/month, and the anchoring value was defined as the upper limit of the respective wage bracket.[12] By utilising the upper brackets, we ensure that we do not offer jobs with

[11] Final-year students amount to less than 10% (N = 3754) of *invitees*.

[12] The "don't know" option was arbitrarily associated with an anchoring value of 3500 EUR/month.

Table 2
Schematic overview of different samples.

Sample	Subsample	Subsample
Invitees (N = 37,950)	Respondents (N = 1852)	Recent jobseekers (N = 1048)
		Current jobseekers (N = 804)
		Reliable respondents (N = 1743)
		Less Reliable respondents (N = 109)
	Nonrespondents (N = 36,225)	
Non-invitees (N = 127,079)		

Notes: Invitees are individuals registered with VDAB in January or February 2021. Non-invitees are individuals registered with VDAB in the period from March to December 2021 (and who did not have an inflow in the first two months of the year).

wages below the respondent's reservation wage. The option to choose a wage category rather than entering a wage was not available to current jobseekers, as we judged that current jobseekers would be less reluctant to indicate their reservation wage than recent job seekers would be to state their actual wage.

On the following screen, we summarised the information provided by the respondent and emphasised that a job encompasses numerous additional characteristics. Subsequently, we asked further questions about their ideal job. These questions pertained to commuting time, working from home, schedule flexibility, and non-wage benefits, all of which played a role in the subsequent choice tasks within the discrete choice experiment. Table A.2 summarises the questions and provides additional information about related studies or surveys that have used very similar questions. The question related to (expected) non-wage benefits is important in the Belgian context where fringe benefits are widespread due to tax advantages.[13]

After completing these tasks, respondents could choose to either conclude the survey or proceed with an additional set of questions. To uphold response quality, the online questionnaire incorporated several checks. These checks were devised to alert respondents when an unusual combination of answers was entered, or even prevent them from entering certain values. For instance, if a respondent had indicated a desire to work more than 60 h per week, they were prompted to adjust their answers to fall below this threshold before proceeding. Similarly, if a respondent indicated a commuting time (round trip) of more than 180 min, a warning message was generated, and values greater than 300 min were not allowed. If a net wage had been entered that implied hourly earnings lower than EUR 5 or higher than EUR 350, a warning message was produced, but the respondents were not forced to stay within this range. However, extreme values serve as indicators of potential response quality issues. Finally, at the end of the survey, each respondent was required to self-rate the reliability of their responses (Dohmen and Jagelka, 2024) on an 11-point Likert scale from 0 to 10.[14]

Respondents are flagged as less reliable if at least one of the following three criteria is met

1. Their self-rated reliability is strictly below 5 on the 11-point scale.
2. Their reported hourly wage is strictly less than EUR 5 or strictly greater than EUR 350.
3. They strongly prefer job 1 in all six choice tasks.[15]

Approximately 6% of respondents were identified as unreliable and subsequently excluded from the analysis.[16] Only in a very small minority of cases (60 observations) the baseline wage for people with a job was based on wage category data.

The survey data were combined with anonymised administrative data from the Flemish PES. This administrative dataset includes standard socio-economic variables such as age, gender, and education. In addition, the Flemish PES collects valuable information from before and during registration, including clients' preferences for occupations, their language proficiency in Dutch (the official language in Flanders), and possession of a driver's licence. The availability of administrative data and registration records for both survey respondents and non-respondents enables us to investigate potential sample selection issues.

3.4. Descriptive statistics

Table A.3 provides descriptive statistics of the baseline job characteristics, which are used as benchmarks for the choice tasks. Among current jobseekers, the hourly net reservation wage is with 13.48 Euro higher than the actual wage of the recent jobseekers. The latter earn on average 11.98 Euro's per hour. Not surprisingly, the standard deviation of the current jobseekers' reservation wage is much higher than that of the recent jobseekers. The average maximum number of minutes current jobseekers are willing to commute (47.60 min) is similar to that of recent jobseekers (48.23 min).

The expectations regarding the schedule flexibility of current jobseekers is very different from the schedule flexibility that recent jobseekers have in their current job. While 55% of the sample of employed individuals have no say in their working schedule, only 23% of the current jobseekers expect to have no say in their schedule in their next job. Current jobseekers expect to have the choice between fixed schedules much more often than has been realised by recent jobseekers in their current job.[17] Also regarding WFH there is a large discrepancy between current and recent jobseekers. While 47% of the current jobseekers are looking for a WFH-feasible job, only 24% of the recent jobseekers is performing such a job. For only 35% of the current jobseekers who look for a job that is WFH-feasible, some flexibility to work from home is actually a requirement. Among those currently in a WFH-feasible job, 43% is working from home 1 day or less per week, while 15% of this group always works from home.

[13] Paying out the monetary equivalent to these 'perks' instead of providing them leads to a higher overall tax burden.

[14] The wording of the question that we used is: "Finally, we would like to present you with the following proposition: My responses to this questionnaire are reliable". Respondents could indicate their agreement on an 11-point Likert scale from 0 to 10 where 0 means 'strongly disagree' and 10 means 'strongly agree'.

[15] Given that the attributes are randomly varied, it is very unlikely that an individual would prefer the first job six times in a row, let alone strongly prefer it.

[16] Given our respondents' characteristics, we deemed it more appropriate to use this approach for identifying potentially unreliable responses, rather than implementing an attention check.

[17] The two groups are much more aligned in terms of (the expectation to have) complete flexibility.

4. Results

4.1. Main analyses

We use conditional logit models to estimate the respondents' preferences for the different attributes in the choice tasks. In these models, a binary dependent variable indicates the preferred job alternative among the two options presented to the respondent. To construct this indicator variable, we follow Maestas et al. (2023) and combine the response options *Strongly prefer job 1* and *Prefer job 1* into one category, signifying a preference for job 1. The other two response options are merged into the category that denotes a preference for job 2.[18]

The respondents are assumed to prefer the job that maximises their utility. The utility that respondent n derives from choosing job j in choice task t is given by

$$U_{njt} = \alpha_j + \mathbf{X}_{njt}\boldsymbol{\beta} + \gamma w_{njt} + \varepsilon_{njt} \tag{1}$$

where $\mathbf{X}_{njt}$ is a vector of non-monetary job attributes and w_{njt} is the wage of job j offered to respondent n in choice task t. $\boldsymbol{\beta}$ is a vector of coefficients to be estimated representing the strength of preference for the non-monetary attributes, γ is a wage coefficient to be estimated and ε is an error term which is assumed to be iid type 1 extreme value. Since there are no differences between the jobs except for the wage and the attributes included in $\mathbf{X}_{njt}$ the alternative-specific constants, α_j, are assumed to be equal for the two jobs, and hence cannot be estimated.

Table 3 shows estimates of the conditional logit models for three different samples. The first pair of columns present results for all *reliable* respondents, the second pair for the subsample of *current* jobseekers, and the final pair for the subsample of *recent* jobseekers, i.e., the ones that were *employed* at the time of the survey.

The wage attribute is expressed in terms of the percentage wage mark-up of the higher-paying job relative to the lower paying job. Specifically, we define the wage attribute, w, in our regression model to be 0 for the job with the lower wage and to be equal to $\frac{w_h - w_l}{w_l}$ for the job with the higher wage, where w_l and w_h denote the wages displayed in the choice experiment for the lower and higher paying job, respectively. By construction, given the way the choice experiments were defined, the lowest wage can never be lower than the wage reported in the survey, i.e., the current wage for the *recent* jobseekers or the reservation wage for *current* jobseekers.

The commuting attribute is represented by two dummy variables indicating reported commuting time being 15 min longer and 15 min shorter than the reported commuting time in the questionnaire, which serves as the baseline. For the attributes of schedule flexibility, possibility of losing one's job, and opportunity to have a social impact, we define dummy variables for each level of the respective job attribute. The least attractive states serve as the baseline in our model, which are respectively *I have no say in my schedule*, *1 out of 100* and *Never*. The WFH-attribute is represented by a set of dummy variables corresponding to each possible level in the choice tasks, with *Never* being the baseline.[19]

The first column in each pair presents the estimated coefficients and standard errors from the conditional logit model. The second column displays the ratios (and their standard errors) of the coefficients to the wage coefficient. These ratios can be interpreted as estimates of the WTP, and absolute values of negative estimates as WTA.

The estimates reveal that individuals derive utility or disutility in all the job search attributes presented. For example, when considering the results for the full sample, the respondents are willing to forego a wage increase of 9% in order to have their daily commuting time reduced by 15 min, while they need a wage increase of 11.6% in order to accept an increase of daily commuting time by 15 min. Likewise, the option to work from home is valued at 15.0% to 19.7% of a monthly wage increase, with more options to work from home being associated with higher willingness to pay. The respondents are also found to value schedule flexibility. In fact, a significant monetary compensation would be needed to accept that the employer has full discretion over the work schedule. Having the choice between a few fixed schedules compared to having no say at all in one's schedule is worth more than a net wage increase of 22.3%. In comparison, the compensation needed for commuting 15 min more is only half this pay difference. Put differently, if we were to assume linearity in the utility function, this means that respondents would be willing to commute 30 min longer per day if they were offered this type of schedule flexibility, suggesting that the search radius of individuals could be increased significantly by offering a few fixed schedules.

Finally, the WTP for job security or to have social impact is substantial. The estimates across different levels and across the different samples range from around 13% to 28% of the monthly wage. This implies that offering job security or a meaningful job might greatly increase the competitiveness of an employer on the labour market. Such job attributes could also help to compensate for less favourable conditions with regards to WFH, schedule flexibility or commuting time. Conversely, given the large negative utility induced by a 20% probability of losing one's job, employers would have to offer substantial improvements in other job attributes in order to compensate for the job uncertainty, such as offering a large degree of flexibility in terms of WFH. Reducing commuting time by 15 min, for example, would not be sufficient to compensate for such a high probability of losing one's job.

The estimates for WTP or WTA are qualitatively similar for both subsamples. There are however modest quantitative differences in the point estimates, and there seems to be a pattern in these differences: the WTP or WTA seems to be somewhat lower across the attributes for employed individuals than for jobseekers. This could be attributed to the fact that there are substantial differences between the two samples, or it could also signal that those who are closest to the job search process have thought through these choices more in-depth.

4.2. Exploiting information on strength of preferences

As described above we have so far combined the response options *Strongly prefer job 1* and *Prefer job 1* into one category to indicate a preference for Job 1, and correspondingly for Job 2. In this section we exploit the information on the strength of preferences by estimating ordered logit models. To implement this approach, we define a new set of variables which represent the differences between the attributes of the two alternatives within each completed choice task. These variables are then used as regressors in an ordered logit model in which the dependent variable is coded from 1 to 4, whereby 1 indicates a strong preference for job A, and 4 a strong preference for job B.[20]

Table A.4 repeats the analyses of the previous table now taking the strength of preferences into account using the above procedure. Generally speaking, the results are qualitatively the same, but the WTP and WTA estimates tend to be somewhat lower in the ordered logit models than in the conditional logit models.

[18] In Section 4.2, we utilise the more detailed information on preference strength using an ordered logit model.

[19] These dummy variables are not included in the model for individuals who have a job that is not WFH-feasible. In the model for the full sample, the WFH-dummy variables are set to 0 for respondents who have a job that is not WFH-feasible, ensuring that the estimates in these regressions only depend on the data from those who have or aspire a WFH-feasible job.

[20] Implementing this approach on the collapsed response categories implies that the ordered logit model collapses to a standard binary logit model as there are only two response categories. Estimating this model replicates the conditional logit results in the previous subsection, so the two estimation approaches are very closely linked.

Table 3
Main conditional logit analysis: Job attribute preferences.

	Whole sample		Current jobseekers		Recent jobseekers	
	Coef.	WTP	Coef.	WTP	Coef.	WTP
% wage increase	3.942*** (0.150)		3.423*** (0.223)		4.359*** (0.205)	
Commuting time: baseline = reported commuting time						
Commute −15 min	0.354*** (0.061)	0.090*** (0.015)	0.317*** (0.091)	0.093*** (0.026)	0.380*** (0.082)	0.087*** (0.018)
Commute +15 min	−0.458*** (0.061)	−0.116*** (0.015)	−0.496*** (0.091)	−0.145*** (0.026)	−0.432 *** (0.083)	−0.099 *** (0.018)
WFH: baseline = no possibilities to WFH						
At least 1 day	0.592*** (0.107)	0.150*** (0.027)	0.641*** (0.138)	0.187 *** (0.041)	0.490*** (0.168)	0.112 *** (0.039)
At least two days	0.695*** (0.106)	0.176*** (0.027)	0.567*** (0.138)	0.166 *** (0.039)	0.835*** (0.168)	0.192*** (0.038)
As much as I want	0.778*** (0.109)	0.197*** (0.027)	0.784*** (0.141)	0.229*** (0.040)	0.700*** (0.171)	0.161*** (0.039)
Schedule flexibility: baseline = no say in schedule						
Various fixed schedules	0.880*** (0.071)	0.223*** (0.018)	0.916*** (0.112)	0.267*** (0.033)	0.860*** (0.092)	0.197*** (0.021)
Can ask changes	0.841*** (0.076)	0.213*** (0.018)	0.882*** (0.119)	0.258*** (0.032)	0.827*** (0.098)	0.190*** (0.021)
Complete flexibility	0.758*** (0.070)	0.192*** (0.017)	0.857*** (0.111)	0.250*** (0.031)	0.701*** (0.091)	0.161*** (0.020)
Chance of losing job: baseline = 1 out of 100						
10/100	−0.621*** (0.071)	−0.157*** (0.018)	−0.731*** (0.113)	−0.214*** (0.034)	−0.560*** (0.093)	−0.128*** (0.021)
20/100	−0.766*** (0.072)	−0.194*** (0.017)	−0.812*** (0.114)	−0.237*** (0.031)	−0.752*** (0.094)	−0.173*** (0.020)
Possibility of having social impact: baseline = never						
From time to time	0.689*** (0.068)	0.175*** (0.017)	0.718*** (0.108)	0.210*** (0.031)	0.681*** (0.087)	0.156*** (0.020)
Always	0.785*** (0.074)	0.199*** (0.018)	0.951*** (0.116)	0.278*** (0.033)	0.674*** (0.096)	0.155*** (0.021)
Observations	20,396		8858		11,538	

Notes: Regression results are displayed for the entire sample of reliable respondents, and then split out for those who are still looking for a job (current jobseekers) and those who have found a job (recent jobseekers), respectively. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Preference heterogeneity

In the previous two subsections we have estimated average preferences for the job attributes for all respondents, as well as for the subsamples of respondents who have found a job already (*recent jobseekers*) and those who have not (*current jobseekers*). It is likely that preferences are heterogeneous also along other dimensions, however. Contrary to previous work, which looks at heterogeneity in preferences by splitting the sample into subsamples based on widely studied characteristics in labour economics and the social sciences in general, we have opted for a data-driven approach using latent class models. These models divide respondents endogenously into groups or classes, where preferences are allowed to vary across classes and assumed to be the same within each class. The latent class model is therefore an extension of the standard conditional logit model, which estimates different coefficients for each class of respondents. While the class membership of each respondent is not known, the probability of belonging to each class can be estimated.

The latent class conditional logit model that we run on the full sample of reliable respondents reveals that observations can be categorised into two main classes.[21] The estimated class membership probabilities imply that the majority of people (70%) belong to class 2, while the rest (30%) belong to class 1. Individuals belonging to class 1, which as explained are a minority of the respondents, are more concerned about remuneration than individuals in class 2. Estimates for WTP and WTA for class 1 are consequently more modest, as the estimated coefficients displayed in Table 4 show. In this class, individuals would prefer a wage increase larger than 4.2% rather than commuting 15 min less per day, and it would be acceptable for them to commute 15 min more if they get a net pay rise of above 5.8%. Other WTP and WTA estimates also are around these magnitudes, but working from home and schedule flexibility seem to be the attributes people are willing to pay most for; more flexibility is found to be equivalent to a wage increase of about 8%.

Individuals in class 2, which constitutes a majority of 70%, put much more weight on non-monetary job characteristics. Once their baseline wage is met, they are willing to forego large wage increases in return for favourable non-monetary conditions. For example, their WTP (WTA) for decreasing (increasing) daily commuting time by 15 min is more than 19% and they are willing to forgo wage increases of up to 40% to have more flexibility in working from home. Having complete schedule flexibility, or having the potential to have a large social impact all the time, are valued at a wage increase of around 50%. Given that the wages in our choice task varied from 1 to 1.5 times the baseline wage, people tend to prefer having these non-monetary job characteristics (compared to the baselines of having no say on

[21] The model is estimated in Stata using the *lclogitml2* command (Yoo, 2020).

Table 4
Willingness to pay for Job attributes by class of latent class model.

	Class 1	Class 2
Commuting time: baseline = reported commuting time		
Commute −15 min	0.042***	0.191***
	(0.010)	(0.038)
Commute +15 min	−0.058***	−0.199***
	(0.010)	(0.035)
WFH: baseline = no possibilities to WFH		
At least 1 day	0.071***	0.201***
	(0.025)	(0.069)
At least two days	0.034	0.402***
	(0.024)	(0.075)
As much as I want	0.074***	0.438***
	(0.019)	(0.076)
Schedule flexibility: baseline = no say in schedule		
Various fixed schedules	0.086***	0.418***
	(0.016)	(0.053)
Can ask changes	0.073***	0.453***
	(0.013)	(0.054)
Complete flexibility	0.036***	0.498***
	(0.014)	(0.060)
Chance of losing job: baseline = 1 out of 100		
10/100	−0.019	−0.390***
	(0.015)	(0.057)
20/100	−0.073***	−0.397***
	(0.012)	(0.048)
Possibility of having social impact: baseline = never		
From time to time	0.026**	0.415***
	(0.013)	(0.057)
Always	0.005	0.553***
	(0.014)	(0.067)

Notes: Latent class conditional logit model estimated on the full sample of reliable respondents, of whom 30% are estimated to belong to class 1 and 70% to class 2. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

the schedule, or having no social impact, respectively) instead of any proposed wage increase.[22]

A second route to exploring heterogeneity in WTP makes use of a subset of individuals, and is focused around the WFH-attribute. In the first part of the questionnaire, we ask current jobseekers whether they are looking for WFH-feasible jobs and, if they reply yes, we also ask whether working from home is a requirement. Less than half of them cite the possibility of WFH as a requirement. We conducted a split sample analysis for people looking for WFH-feasible jobs, distinguishing between those who answered either yes or no to the requirement-question. Table 5 shows three columns, the first two corresponding to the WTP estimates of the respective subgroups, and the third displaying the *p*-value at which the null hypothesis of equal WTP can be rejected. The results suggest that the differences are very substantial. The WTP for working from home is much higher in the sample of those who indicated it as a requirement, and the WTP in this latter sample also increases strongly over the different WFH categories, whereas this is not the case for the other group. Thus, the results in this table indicate heterogeneity in preferences, but could also be seen (at least to some extent) as evidence for the cross-validation of the two methods of eliciting preferences, either through direct questioning or through choice experiments. There are also interesting differences in other domains. For example, jobseekers who are not concerned about working from home are much more concerned about job security.

[22] The set-up of our experiment does not allow us to investigate to what extent people are willing to go below their reported wage in the survey.

Table 5
Split-Sample Analysis: Willingness to Pay for Current Jobseekers With and Without a WFH Requirement.

	WTP (Req)	WTP (No Req)	P-value
Commuting time: baseline = reported commuting time			
Commute −15 min	0.07	0.13	0.273
Commute +15 min	−0.11	−0.13	0.770
WFH: baseline = no possibilities to WFH			
At least 1 day	0.24	0.11	0.054
At least two days	0.26	0.10	0.012
As much as I want	0.42	0.08	0.000
Schedule flexibility: baseline = no say in schedule			
Various fixed schedules	0.23	0.29	0.502
Can ask changes	0.22	0.22	0.972
Complete flexibility	0.28	0.32	0.721
Chance of losing job: baseline = 1 out of 100			
10/100	−0.01	−0.17	0.069
20/100	−0.08	−0.24	0.076
Possibility of having social impact: baseline = never			
From time to time	0.15	0.22	0.455
Always	0.19	0.30	0.216

Notes: In the survey we ask jobseekers who aim for a job that is WFH-feasible whether or not WFH is a requirement. This table contrasts the WTP of individuals who answer yes vs. no to this latter question. Estimations are based on a pooled split-sample regression, with observations for 369 jobseekers looking for WFH-feasible jobs, out of whom 134 state that the possibility to work from home is a requirement.

4.4. Sample selection and nonresponse

As explained in Section 3.2, the *respondents* only constitute a fraction of all *invitees*, and among these respondents there is also a small subset of less reliable respondents whom we omit from the analysis. In addition, the invitees registered with VDAB at a specific time in the year, which could mean that they are not representative of the entire population of individuals who had an inflow that year due to seasonality effects.

To investigate to what extent the samples are different from each other, we ran probit models predicting sample membership, which are presented in Table A.5. The results show that there are statistically significant associations between sample membership and the individual characteristics derived from the administrative data. For example, individuals with a university degree or with high proficiency in Dutch are much more likely to be respondents than others. The results also show that there is a difference in sample composition between invitees and non-invitees, and between the reliable respondents and all other invitees and non-invitees. Age, being female, being registered out of work for 12+ months (out of the last 3 years), having a driver's licence, schedule and sector preferences are all significant predictors for being an invitee or reliable respondent versus a non-invitee.

To explore what the effects of such sample selectivity could be on the results from the choice experiments, we created a set of inverse probability weights. In order to create the weights, we run similar models again as displayed in Table A.5. However, we employ the k-fold cross-validation method for out-of-sample probability predictions. Specifically, the individual sample is divided into five groups of equal size, denoted as i_1 to i_5. Subsequently, five Probit regressions, indexed $j = 1 \dots 5$, are run on the sample excluding observations from group i_j. The coefficients estimated from regression j are then used to predict the probabilities for subsample i_j. A complication is that the size of the samples we compare with each other are far from equal. For example, less than 5% of invitees are reliable respondents. Consequently, the predicted probabilities are generally quite low, leading to huge differences in inverse probabilities when differences of only a few percentage points are observed, which means that a few observations may become disproportionately influential. To mitigate this issue, we adopted the approach discussed by Chesnaye et al. (2021) and multiplied the inverse probabilities by the success rate, or, in this case, the proportion of individuals in the estimation sample for which we predict membership. This adjustment not only reduces the average inverse probability weights but, more critically, also diminishes their variation.

In Table 6 we run various specifications exploring sample selection. The first specification shows the results of an unweighted regression on data from all *respondents*, while the second specification restricts the sample to *reliable* respondents and is therefore identical to the first specification in Table 3. The last two columns show results from specifications run on the *reliable* respondents, but now weighting the observations for non-response and for non-response or not invited, respectively.

The results are qualitatively quite similar. However, after applying sample weights, the point estimates of WTP for the flexibility attributes (WFH and schedule flexibility) are consistently higher than in the first two columns. Of course, there is a caveat here, as we can only correct for a selected number of observed variables, and the variation in preferences may be greater than our results suggest. The membership predictions show that there are certain groups that are more likely to respond, which can guide future policy-oriented research to make additional efforts to target such groups and elicit their preferences.

5. Concluding discussion

Over the last decades and years, labour markets have undergone significant changes. Persistent shocks to labour demand and labour supply are likely to lead to a substantially different labour market in the long run, with shifts in job tasks and skills prices (Acemoglu and Autor, 2011; Barrero et al., 2020), but also in the organisation of work. New technologies provide new opportunities for remote work or scheduling flexibility. To the extent that such job attributes are valued by workers, it is important for firms and policymakers to know how these attributes affect the acceptability of jobs, i.e., what bundle of attributes constitute a reservation job, and how these attributes are valued in monetary terms.

This project provides a snapshot of estimated monetary values of such important job attributes for individuals who became eligible for UI in January or February 2021. At the time of the interview, some had already secured a job, while others were (again or still) seeking employment. In line with other studies, we find that the willingness to pay for various job attributes is positive and significant. Compared to previous studies, our estimates tend to be at the higher end of the range of estimates for WTP or WTA across studies documented in Table A.1. This range of estimates can be quite large, depending on the actual trade-off that participant in the different experimental studies are asked to make (e.g., 0 min of commute versus 15 min, or 0 min versus 60 min) or on the subgroup analysed.

The estimated WTP and WTA in our study may be higher than those typically found in the literature due to a combination of several factors, including demographic and socioeconomic factors, survey design and methodology, or framing and contextual factors. First, we worked with individuals who have been actively undergone the job search process, rather than relying on a convenience sample from an Internet panel. Second, the choice experiments were highly personalised: work-from-home options were only presented to those for whom it was relevant, and parameters such as wage and commuting time were anchored to realistic values specific to each respondent. Third, our heterogeneity analysis employed latent class models, making it more data-driven compared to traditional split-sample analyses based on socioeconomic characteristics. Lastly, while we ensured that the wage attribute never fell below the respondent's reported wage for ethical reasons, we included a wide wage range up to 1.5 times the reported wage, which is significantly broader than what is typically found in the literature.

The insights about workers' valuations of job attributes can inform labour market and firm policies. For example, our results indicate that offering flexibility in terms of WFH or schedule flexibility, could provide an alternative to increasing wages or to compensate for deteriorating job attributes in other dimensions, e.g. when perceived job loss risk increases in particular sectors or firms due to technological change.

Job search theory implies that frictions in the labour market could be reduced if jobseekers increase their search radius or their willingness to commute longer. Our results suggest that the search radius of individuals could be increased substantially by offering increased schedule flexibility or the possibility of working from home. Our experimental design enables differentiation between increases and decreases in commuting time from a baseline level, as reported in the survey. Notably, these differences appear to be most pronounced when respondents are asked to expand their commuting radius from the baseline. This offers an important insight, particularly when formulating policies aimed at bolstering labour market participation within specific demographic cohorts.

Moreover, improving schedule flexibility, opportunities to work from home or increasing job security could also contribute to reducing regional skill mismatches by attracting commuters from other areas. In areas experiencing a skills mismatch between supply and demand, attracting skilled individuals by paying higher wages alone may be challenging due to the considerable monetary compensation required for commuting. For example, an increase in the commuting time for the average respondent by only 15 min would have to be compensated by a net wage increase of almost 12%. Latent class models show that there is substantial heterogeneity and that a majority of respondents would even need larger wage compensation. Similarly, job insecurity driven, for example, by technological change, requires substantial wage compensation. In such cases, firms may benefit from adopting alternative strategies to meet their demand, for instance by considering the entire bundle of job characteristics and instead of solely relying on wages in their compensation package firms could promote non-monetary

Table 6
Willingness to pay for job attributes: Exploring nonresponse and sample selection.

	Full sample	Reliable respondents	Weighted for nonresponse	Weighted for nonresponse or not invited
Commuting time: baseline = reported commuting time				
Commute −15 min	0.096***	0.090***	0.092***	0.098***
	(0.015)	(0.015)	(0.017)	(0.020)
Commute +15 min	−0.113***	−0.116***	−0.148***	−0.135 ***
	(0.015)	(0.015)	(0.017)	(0.021)
WFH: baseline = no possibilities to WFH				
At least 1 day	0.133***	0.150***	0.189 ***	0.214***
	(0.028)	(0.027)	(0.031)	(0.037))
At least two days	0.172***	0.176***	0.228***	0.250 ***
	(0.027)	(0.027)	(0.030)	(0.035)
As much as I want	0.174***	0.197***	0.255***	0.275***
	(0.027)	(0.027)	(0.031)	(0.037)
Schedule flexibility: baseline = no say in schedule				
Various fixed schedules	0.223***	0.223***	0.249***	0.255***
	(0.018)	(0.018)	(0.021)	(0.025)
Can ask changes	0.218***	0.213***	0.232***	0.231***
	(0.018)	(0.018)	(0.020)	(0.024)
Complete flexibility	0.192***	0.192***	0.243***	0.250***
	(0.017)	(0.017)	(0.020)	(0.024)
Chance of losing job: baseline = 1 out of 100				
10/100	−0.167***	−0.157***	−0.163***	−0.181***
	(0.018)	(0.018)	(0.022)	(0.025)
20/100	−0.204***	−0.194***	−0.219***	−0.224***
	(0.017)	(0.017)	(0.020)	(0.023)
Possibility of having social impact: baseline = never				
From time to time	0.168***	0.175***	0.194***	0.202***
	(0.017)	(0.017)	(0.021)	(0.024)
Always	0.198***	0.199***	0.242***	0.272***
	(0.018)	(0.018)	(0.022)	(0.026)
Observations	21,470	20,396	19,428	15,834

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The results in the first two columns are based on the sample of all respondents and the sample of reliable respondents respectively. The results in the last two columns are again based on the sample of reliable respondents, but with sample weights applied. As only a minority of those invited to the survey respond, the third specification corrects for non-response. Non-invitees had an inflow in 2021 but not in January and February, while invitees had at least one inflow in January or February. The final specification therefore corrects for selection by non-response and non-invitation.

amenities such as corporate social responsibility and offer meaningful jobs with flexible work schedules and remote work opportunities. In case of regional skill mismatches, advertising job stability and long-term employment prospects might also help in attracting commuters from other regions by advertising and offering other amenities that are linked to the job.[23] Potentially, firms might contribute to higher social welfare by offering these non-monetary job amenities as an alternative to increasing wages.

CRediT authorship contribution statement

Bert Van Landeghem: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Thomas Dohmen:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Arne Risa Hole:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Annemarie Künn-Nelen:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

[23] While offering jobs with high job security is probably easiest in the public sector, also competitive firms could emphasise the prospects of permanent jobs after some time in temporary employment.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.labeco.2024.102631.

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