Matching with preferences: Caring who cares for the old

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Abstract

This paper examines preferences over caregiver and care recipient characteristics in home-based long-term care, using unique data from a matching agency on households' and workers' ex-ante preferences, realized matches, wages, and job durations. I estimate a matching model to quantify each party's valuation of match attributes as a function of preferences, and their impact on employment stability. Linking the data to population registers shows that demand is rising fastest where preferences over workers' origin are stronger, while gender preferences will weaken. Simulations predict welfare changes under varying worker compositions, suggesting modest losses from a shift toward more distant immigrant workers.

Keywords: employer preferences, immigration, matching.
JEL Classification: I1, J1, J6.

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1 Introduction

Aging populations make long-term care provision one of the most pressing social and economic challenges of our time. Roughly half of elderly individuals receiving care in Europe rely on privately employed, often immigrant, live-in caregivers.[1] These intimate arrangements imply an important role of trust and families' preferences over workers' personal characteristics such as gender or origin. Well-matched caregiver–recipient pairs can raise surplus and reduce turnover, which is costly for all sides. Despite the scale of the issue and the welfare implications for both care recipients and their families, little is known about how individual preferences shape match values and the stability of employment relationships.

This paper is the first to document households' explicit preferences over caregivers' characteristics and to quantify their consequences for payoffs and employment stability. Despite a frequently stated preference against immigrant workers from distant origins, the welfare effects of shifting towards distant migrants are small relative to the overall surplus generated. I study Italy, one of the world's oldest populations, where typically workers are employed directly by care recipient households. I use internal data from an agency specialized in matching households with—typically full-time—care workers. These data contain unique information about the agency's clients and their preferences over a care worker's age, gender and origin, as well as workers' ex-ante preferences over care recipients' gender, cognitive and physical health condition.[2] Linking these stated preferences to realized matches, wages, and job durations, I estimate a structural one-to-one matching model that recovers valuations of match characteristics for both care recipients and workers, as well as the costs of preference violations.

I merge the agency data with longitudinal population registers to examine how demographic change will affect future demand and welfare in this important sector. I project the growth of the elderly population across municipalities and demographic groups through 2040. Whereas currently 34 percent of agency clients state a preference for European over non-European care workers, this share is markedly higher in the municipalities that are expected to see the strongest growth in elderly populations. Yet, as the main origin countries of care workers in Eastern Europe experience fast demographic change on their own, their capacity to meet

[1] Survey of Health, Ageing and Retirement in Europe (SHARE, see Börsch-Supan et al., 2013) data show trends towards paid care at home across many European countries (see Appendix Figure A1). Mommaerts and Truskinovsky (2020) report that 37% of formal care recipients in the United States receive these services at home, often complemented by informal family care.

[2] A comparison with nationally representative SHARE data shows very similar observed characteristics, see Appendix Table A1.

increasing demand in Western Europe will be limited. Scaling model predictions by population registers and survey data capturing the reliance on home-based care allows me to quantify the welfare effects a shift towards non-European care workers would have. Compared to an optimally composed worker pool, exclusive reliance on non-European workers would reduce the aggregate welfare of care recipients by only 0.7 percent. This small loss stands in contrast to the high share of agency clients stating a preference for European workers, highlighting the need to distinguish expressed preferences from the weight they carry in agents' utility. Cross-sectionally, stated preferences do not significantly vary with local population compositions, suggesting that preference do not easily change with exposure.

Most female, but also 70 percent of male care recipients or their families ("clients" of the agency) prefer female carers. The data thus highlight matching based on preferences as an essential refinement over assortative matching between care recipients' and carers' own gender. The population registers reveal that the share of men in the elderly population is expected to grow, suggesting a weaker future bias toward female carers.[3] On the worker side, most carers are ex-ante available to work with both men and women, although 12 percent state a preference for female patients. The model identifies distinct payoffs that specific sex-combinations and stated preferences can have for carers and care recipients.

These are important distinctions from commonly estimated one-to-one matching models as developed in the literature on marriage markets (Choo and Siow, 2006; Dupuy and Galichon, 2014; Goussé et al., 2017; Chiappori, 2020; Ciscato et al., 2020; Galichon and Salanié, 2022; Gualdani and Sinha, 2023; Adda et al., 2025).[4] The general structure of these models lends itself well to estimating match valuations, incorporating the unique information on agents' preferences available in the data. In particular, the value of any given match relative to the value of alternative matches is identified from relative match frequencies for different types of caregiver-recipient pairs. This allows identification of most model parameters based solely on data from agents matched by the agency, avoiding the need to rely on the incompletely observed population that is matched through other channels

[3]I find no evidence that expressed preferences vary by care recipients' cognitive status. This suggests that there is no major difference between the preferences over worker types held by relatives, who likely fill in the questionnaire on behalf of care recipients suffering cognitive decay, and by healthier care recipients, who may help filling in the questionnaire.

[4]Only a small part of the parallel literature on matching in the labor market considers matching on multiple dimensions (see in particular Lindenlaub, 2017), as I do here. An important distinction is that, in the spirit of the marriage market literature, I consider match-specific returns to workers beyond wages. A further difference compared to Lindenlaub (2017) is that matching in my model is based on both observed and unobserved heterogeneity.

or reliant on alternative care arrangements.

The model I estimate distinguishes itself from models of the marriage market in three fundamental ways. First, whereas models of marital sorting often assume transferable utility,[5] transfers are typically unobserved. As a result, only total match values are identified, not their allocation across partners. In my context, observed wages provide a (potentially imperfect) measure of transfers[6] which, building on Dupuy and Galichon (2022), makes it possible to determine how variation in match characteristics affects each side's payoff separately.

Second, the availability of ex-ante preferences is an important refinement over matching on observed characteristics only. In addition to the imperfect correlation between own gender and gender preferences previously described, direct preference information also is important because for some characteristics there is meaningful variation only on one side of the match. For instance, whereas national origins vary across workers, nearly all care recipients are Italian. Conversely, strong cognitive or physical impairment is found only among care recipients, not workers. Note also the difference between my focus on estimating the payoffs from different matches versus the analysis of sorting patterns that much of the literature on marriage markets is concerned with (in addition to the papers cited above, see also Chiappori et al., 2018; Gihleb and Lang, 2020; Calvo et al., 2024).

Third, identification of the level of a match surplus in the marriage market literature relies on the observation of singles. Internal company data of the kind used in this paper naturally do not adequately cover the populations of unmatched agents. In the model, information on matched parties identifies the relative values of different matches, not the level of the surplus. To identify the latter, I make match duration and dissolution an explicit part of the model. This is important also because it accounts for variation in outside options of households and workers that lead to different equilibrium transfers and separation rates.

In the context analyzed here, preferences may be violated not because of inefficient matching, but because matching is on multiple dimensions and the pools of clients and workers are finite. Subject to the available pools, the matchmaker's objective is to maximize the aggregate duration of contracts. Moreover, the matchmaker always assigns clients a worker even if only some of the preferences can be met. Hence, there is no incentive to strategically state false preferences.[7]

[5]That assumption is relaxed, for instance, by Gayle and Shephard (2019) in a model in which equilibrium marriage matching is followed by resource and time allocations.

[6]The model allows for wages to be an imperfect measure of transfers to account, for instance, also for under-reported and uncompensated work hours or in-kind transfers.

[7]Empirically, I also do not observe a benefit for clients in stating indifference towards worker

The vast majority of matches have full-time employment contracts and 79 percent of workers co-reside with care recipients, so that a one-to-one care relation is the norm. Whereas the data used in this paper provide novel insight into the preferences of caregivers and recipients, the structurally estimated model in conjunction with observed matches and their durations quantifies the *importance* of these preference statements in terms of their potential effects on surplus and employment stability. The payoff from being matched with a male worker is reduced by a sizable 0.64 euros per hour when clients have a preference for female workers, equivalent to 11 percent of the median hourly wage of 5.85 euros. Such a mismatch reduces employment duration by 4.4 percent. Clients with a preference for European workers suffer an hourly loss equivalent to 2.5 percent of the median wage when matched with a non-European worker.

While most clients prefer female workers in their 40s or 50s, the payoff to clients who are indifferent to a worker's age and gender is actually higher for younger and male workers. I thus obtain a differentiated picture, where young and male workers who select into care work are not less productive, but in which most clients' preferences are biased towards older and female carers.

The empirical results in this paper show that matches generate a higher payoff for clients with care recipients diagnosed with Alzheimer's disease, indicating that private live-in care is preferred to alternative care arrangements. The opposite is true for bedridden patients, who may be more likely to require institutional care.

My surplus estimates speak to studies quantifying the welfare effects of long-term care, such as Costa-Font and Vilaplana-Prieto (2025). I estimate that in 2022, private home care generated an aggregate surplus of 6.7 billion euros, which considerably exceeds financial expenditure, for which estimates are available. Aggregating my data, expenditure on private home care amounts to 3.7 billion euros per year. Relative to GDP (0.19 percent), this estimate is similar to the 0.15 percent of GDP reported by Geyer et al. (2025) for Germany, but higher than estimates for countries with younger populations, such as England (Banks et al., 2025) or the U.S. (Gruber and McGarry, 2023).

This paper also contributes to several strands of research in health and labor economics, including the role of immigration in care provision, as well as employer preferences and discrimination. Immigration has been linked to elderly care both through its effect on the availability and quality of care services and through the downstream effects on labor market outcomes for family members, most notably daughters. Furtado and Ortega (2023) document a direct link between immigra-

characteristics in terms of waiting time until a match is formed.

tion and the supply of labor to nursing homes, as well as better patient outcomes. Almuhaisen et al. (2023) show that stricter immigration enforcement reduces the supply of household service workers, leading to an increase in institutionalized care for elderly individuals. Haan and Wnuk (2024) find that increased foreign staffing alleviates labor shortages in long-term care and improves working conditions for natives. Frimmel et al. (2025) show that declines in parental health negatively affect the labor market outcomes of adult children, but these effects are significantly weakened when migrant care workers expand the availability of formal care.

Other related literature examines the choice of care arrangements. Mommaerts (2018) studies the impact of nursing home costs and finds that lower out-of-pocket expenses for institutional care reduce the prevalence of co-residence with adult children. The substitutability between formal and informal care also is examined by Ko (2022), who estimates the value of pricing long-term care insurance based on information about adult children of insured individuals. Barczyk and Kredler (2018) model care choices as a dynamic game and show that they respond strongly to different types of subsidies. Montesinos (2025) examines the choice between care modes across European countries, and finds that institutional factors explain much of the differences between informal and formal care. Maestas et al. (2024) study the labor market effects of family caregiving and find that it leads to declines in employment and earnings for women, while men tend to take on caregiving roles only after experiencing job disruptions.

Employer preferences over workers' personal characteristics are investigated by Flabbi (2010), who develops a search model that incorporates employer taste discrimination in the labor market and shows that even unprejudiced employers engage in wage discrimination based on gender. Kuhn and Shen (2013) analyze explicit gender preferences in job ads on a Chinese online job board, finding that employers have idiosyncratic preferences for gender-job matches. Expanding on this, Kuhn and Shen (2023) study the effects of removing gender preferences from job ads and find that this led to more gender-diverse applicant pools. Relatedly, Card et al. (2025) examine an Austrian ban on explicit gender preferences in job ads and find that this policy increased the hiring of women in male-dominated jobs and vice versa. The literature on racial discrimination in labor markets is reviewed by Lang and Kahn-Lang Spitzer (2020). Hurst et al. (2024) examine racial discrimination through a task-based model of occupational sorting. Different from this literature, I quantify how preferences affect employer and worker payoffs and employment duration, using a matching model estimated on novel data from a sector central to aging societies.

2 Data and descriptives

Preferences of households employing[8] care workers over these workers' personal characteristics are not observed in administrative or survey data. Private companies, however, elicit such preferences in order to tailor their services.

Data source. The main dataset used in this study was compiled from internal records of an Italian company that specializes in matching elderly care recipients with care workers. The data cover characteristics and preferences of the company's clients (the households to employ a care worker), matches, and employment terminations from January 2020 to June 2023. The company maintains a database of potential care workers, who in turn state their preferences over working with different types of care recipients. Caseworkers employed by the company are tasked with forming matches based on client requests, accounting for stated preferences on both sides.

Client data are extracted from detailed questionnaires that collect information on the care recipient's health status and care needs. The last page of the questionnaire (displayed in Appendix B) furthermore inquires about specific preferences regarding care workers' age, sex, and origin. Similarly, the worker database contains detailed demographic and professional characteristics of potential caregivers, along with their availability for working with bedridden or Alzheimer's patients, and their willingness to work with male or female patients. This information is collected through an online mask on the company's website. As I observe some matches violating workers' stated availabilities, I interpret this information as preferences rather than hard constraints.

Legal framework. The company's services include administrative support for the employment of a worker. When matched, clients thus sign both an employment contract with the worker and a contract with the company. The latter includes a non-compete clause over three years which prevents clients from employing a worker while circumventing the company. The legal basis for discrimination on age, sex and origin through the questionnaires filled in by clients are exemptions from non-discrimination specified in legislative decree number 216, article 3 (see Appendix C). Note that the company data include only formal employment con-

[8]Throughout the paper, I refer to the employer side interchangeably as "clients", "care recipients", "households" or "patients".

tracts.[9] For parameter identification under the model presented in Section 3 this is not a problem, since, as explained below, the estimation requires data on matched agents only.

2.1 Patient and worker characteristics and preferences

The analysis focuses on characteristics of either care recipients or care workers for which the data contain preferences on the respectively other side.

Care recipient characteristics. Table 1 lists the main characteristics and preferences of care recipients across all matches formed between January 2020 and June 2023.[10] On average, care recipients are in their mid 80s, 70 percent are female. Regarding health conditions, 11 percent of clients have been diagnosed with Alzheimer's disease, while 8 percent are bedridden. Panel (a) of Figure 1 displays the age distributions of care recipients and workers. Appendix D provides further descriptives, including the full distributions of cognitive and mobility status (Figure A5). My analysis will focus on Alzheimer's diagnosis and being bedridden as the categories for which I observe workers' availability (more on this below).

Representativeness. While client data from a non-monopolistic firm by construction are not representative of an entire market, Appendix Table A1 shows that care recipients' characteristics are very similar to respondents to the nationally representative SHARE data when conditioning on the presence of a paid care worker at home. The table also shows that in comparison to recipients of other types of care, which in Italy primarily is informal care by family members, those with a live-in care worker tend to be older and in worse health. Despite these differences, a key advantage of the data used here is their detailed information about clients' preferences. Representative survey data on discriminatory preferences (if available at all) would be prone to non-responses, which in the company data are minimal (see the low variation in the number of observations in Table 1).

Client preferences. Stated preferences regarding worker characteristics suggest that only 5 percent of clients prefer workers aged 20 to 40, while most clients

[9] A comparison between reliance on private care workers reported in survey data and the aggregate number employees in this sector recorded in Italian social security data suggests that about half of employment in this sector is undocumented.

[10] Despite the pandemic, the data do not exhibit any major time trends. Appendix Figure A3 shows that coefficients from separate regressions of care recipient characteristics and preferences on calendar year are small and mostly insignificant.

(57 percent) favor older caregivers. The remaining 37 percent of clients are indifferent regarding a worker's age. Gender preferences are strongly biased towards female caregivers. Note that the share of 88 percent stating a preference for female carers strongly exceeds the share of female care recipients. Only 3 percent explicitly prefer a male worker. More than one third of clients prefer European workers, while 7 percent specifically request a non-European caregiver.[11] Client preferences over the full set of worker origins listed in the questionnaire are displayed in Figure 1b. In Table 1, as well as in the model, clients are classified as preferring a European worker if in the questionnaire's section on preferred worker origins they select Europe, but none of the other origins nor the indifference option; as preferring a non-European worker if they select at least one of the non-European origins, but neither the Europe, nor the indifference option. All other clients (selecting indifference and/or both Europe and at least one non-European origin) are classified as not having a strict preference for European or non-European workers.

Table 1: Client characteristics and preferences

	Mean	**Std. Dev.**	**Obs.**
Age	83.516	8.930	2724
Female	0.696	0.460	2748
Alzheimer	0.108	0.310	2726
Bedridden	0.083	0.277	2708
Prefers care worker who is			
Aged 20-40	0.052	0.223	2662
Aged 40-60	0.575	0.494	2662
Female	0.885	0.319	2726
Male	0.032	0.175	2726
European	0.342	0.475	2693
Non-European	0.070	0.256	2693

Note: This table shows summary statistics for care recipients' characteristics and preferences regarding care workers for all matches formed between January 2020 and June 2023. The bottom panel lists explicitly stated preferences over caregiver attributes, with the remaining shares pertaining to indifference between the categories. Source: Firm administrative data.

Truthful reporting of preferences by clients. Since clients are always assigned a worker, there is no incentive to strategically state false preferences.

[11] A possibility is that requests for non-European caregivers derive from expected lower pay (gross hourly wages paid to non-European workers in fact are only 0.5% lower wages paid to Europeans). While I do not observe clients' income, the agency collects information on the apartment size of the care recipient. Appendix Figure A4 does not support the notion that non-European workers are demanded disproportionately by clients with smaller apartments.

The records also show no significant difference in the time it takes to finalize a contract, part of which involves the time to find a worker. The data record the date at which a caseworker start searching for a worker as well as the date when a contract is signed. Appendix Figure A6 shows the cumulative distribution of this time. On average, it takes less than two weeks to form a match, with a yet shorter median duration. The figure shows that there is no meaningful difference between matches where clients were indifferent over a worker's age, gender and origin, and those where clients express a preference regarding at least one of these dimensions. For the latter group, the median time until a match is formed is a mere two days shorter. While time until match formation is not used in the structural estimation of the model presented below, these descriptives do not support the notion that clients benefit from withholding their true preferences.

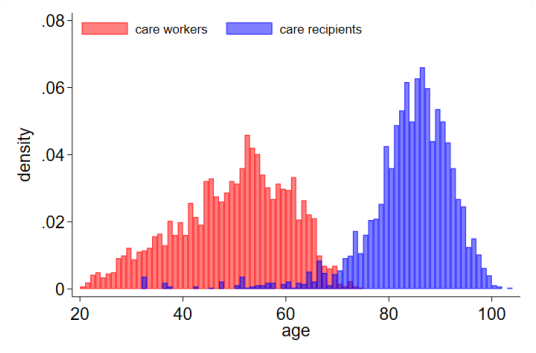
Appendix Figures A7-A9 moreover plot the distributions of client preferences over workers' age, sex and origin by care recipients' physical and cognitive health. The clearest pattern emerges for age preferences by patients' mobility (Panel (a) of Figure A7). Clients more often favor young care workers when patients are bedridden, whereas they are more often indifferent about a worker's age when care recipients are in good physical health. This suggests that clients who are in more urgent need of a care worker do not give up indicating their preferences. There is no systematic variation in clients' preference across care recipients' cognitive status (Panels (b) of Figures A7-A9). This indicates that there is no major difference between the preferences over worker types held by relatives, who likely fill in the questionnaire on behalf of care recipients suffering cognitive decay, and by healthier care recipients, who may help filling in the questionnaire.

Care intensity. Work contracts specify the intensity of care ("CS" in the Italian classifications). My model approximates this by conditioning on care recipients' health. In particular care recipients being bedridden is a strong predictor for intensive care contracts, whereas the other client characteristics listed in Table 1, including age and and Alzheimer's diagnosis, have very little predictive power, see Appendix Table A2. Appendix Figure A10 provides additional detail on the shares of intensive care contracts for each level of a client's physical mobility, including the worst category of being bedridden, for which 85 percent of contracts specify intensive care.

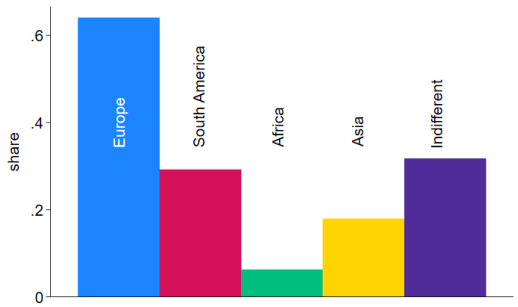
Worker characteristics. Table 2 summarizes the characteristics and preferences of matched workers. Care workers are predominantly female, with an

Figure 1: Age distributions and origin preferences

(a) Age distribution



(b) Client preferences over worker origin



Note: Panel (a) shows the age distributions of care workers and care recipients across all matches formed between January 2020 and June 2023. Panel (b) displays the distribution of client preferences over a worker's origin (multiple choices possible). Source: Firm administrative data.

average age of 49. The dataset reflects the diverse backgrounds of workers: 57 percent of workers are European, with Italians, Romanians, and Ukrainians forming the largest groups. Overall, only about one in six matched care workers are Italian. Among non-European workers, the most common nationalities are Moroccan, Senegalese, and Peruvian.

Worker preferences. Most carers are available for working with both female and male care recipients, but close to 12 percent prefer women. Only 2 percent state that they are available for working male, but not female care recipients. Not all workers declare their availability for working with heavily impaired clients: just above 40 percent of workers indicate availability to care for Alzheimer's and/or for bedridden patients.

Truthful reporting of preferences by workers. A concern may be that workers with less frequently demanded characteristics (such as workers of non-European origin) falsely overstate their availability to work with difficult care recipients (such as Alzheimer's or bedridden patients). To investigate this, I first restrict the sample to matches with workers who reported an availability to work with care recipients diagnosed with Alzheimer's disease and examine whether non-Europeans exhibit a higher probability of quitting the job if indeed they are matched with Alzheimer's patients. Columns (1) and (2) of Appendix Table A3 show that this is not the case (if anything the opposite is true). Columns (3) and (4) repeat this for workers declaring to be available for working with bedridden

Table 2: Worker characteristics and preferences

Variable	Mean	Std. Dev.	Obs.
Age	49.163	10.858	2612
Female	0.923	0.266	2629
European	0.568	0.496	2622
Italian	30.9%		
Romanian	30.5%		
Ukrainian	13.2%		
Non-European	0.432	0.496	2622
Moroccan	15.8%		
Senegalese	13.9%		
Peruvian	12.3%		
Available for work with			
Women	0.116	0.320	2619
Men	0.018	0.131	2619
Is available for			
Alzheimer's patients	0.413	0.492	2619
Bedridden patients	0.427	0.495	2619

Note: This table presents summary statistics for worker characteristics and preferences regarding patients for all matches. The sample includes matches formed between January 2020 and June 2023. Within European and non-European origins the three most frequent nationalities are reported. The bottom panel lists explicitly stated preferences over patient attributes. Source: Firm administrative data.

patients. Similarly, Appendix Tables A4 and A5 consider declared availabilities and quits by young or male workers, who are less often demanded by clients than older and female workers. None of the overall 12 coefficients pertaining to workers with a less demanded characteristics points towards a false over-reporting of availabilities.

2.2 Meeting preferences

Part of the agency's revenue derive a monthly fee for the duration of a contract, which creates an incentive to form matches that respect preferences as far as possible, in order to avoid an early separation and clients seeking alternative care arrangements. Preference violations in my setting can arise despite efficient sorting of clients and workers by caseworkers. The reason are the multi-dimensionality of preferences and the limited size of client and worker pools. Appendix Table A7 shows match quality across different dimensions in terms of how well stated preferences align with observed matches. Throughout this paper, I use the terms "mismatching" and "match quality" to indicate whether expressed preferences

are violated or met. Overall, the Table A7 clearly shows that preferences influence matches. In particular clients', but also workers' gender preferences strongly correlate with the respectively other side's sex. Only the share of bedridden care recipients does not align with workers' stated availability to work with such patients.

2.3 Separations

There is no interview stage or direct selection of workers by households. However, match quality is potentially important for employment stability. The majority of contracts in the data, 82.7 percent, are either open-ended (77.1%) or have been extended at least once (5.7%). The average match lasts 125 days, including 10.8 percent of observations that are censored by the end of the observation window. The median duration across all matches is 41 days, indicating that durations are strongly skewed. Termination reasons vary: 62 percent of separations occur at the client's initiative, either because the worker is dismissed or the contract is not renewed. Worker resignations account for 23 percent of terminations, while client deaths lead to 4 percent of employments ending. The remaining 11 percent of terminations are attributed to other factors, including transfers to institutional care. After a separation, especially when initiated by the client, the latter likely try to find care workers through other sources or choose alternative care arrangements. Hence, more often than not, clients disappear from the firm data after a match is dissolved.

Undocumented continuation. Panel (a) of Figure 2 presents the distribution of match durations by termination reason. Clients sign a contract with the matching company that includes a non-compete clause over three years which prevents clients from employing a worker while circumventing the company. The data also do not suggest that clients terminating formal contracts with the aim of a continued informal employment of the same worker is a widespread phenomenon. As Appendix Table A6 shows, 43% of workers whose employment spell has ended are assigned contracts with new clients, so that they cannot continue informally with a formerly matched client. The mean number of contracts for these workers is three and as expected, a re-assignment during the observation window is more likely if the initial job duration was shorter. The table moreover shows that re-assignment (ruling out informal continuation) is relatively more likely among non-European workers and that there is no difference in formal layoff probabilities

for workers who subsequently are assigned a new contract. The data thus do not support a scenario in which clients terminate a contract soon after a match is formed in order to continue employment informally.

Separations by patient age and health. Panels (b) and (c) of Figure 2 show that the reason for separation that correlates most strongly with care recipients' age or health status is workers' resignation, whereas more "exogenous" separations due to the care recipient's death or other reasons (including transfers to institutional care) do not correlate with care recipients' age or health in the data. Worker quits reflect the low amenity value of being matched with these patients, which the model presented below is designed to identify.

Better matches last longer. Panel (d) of Figure 2 examines employment duration by match quality, distinguishing whether matches meet clients' preferences over workers' age, sex and origin and workers' preferences over care recipients' sex, Alzheimer's and bedridden status—64 percent of matches satisfy all these preferences. The figure shows that contracts where preferences are unmet tend to end sooner, with a difference at median durations of 24 percent.

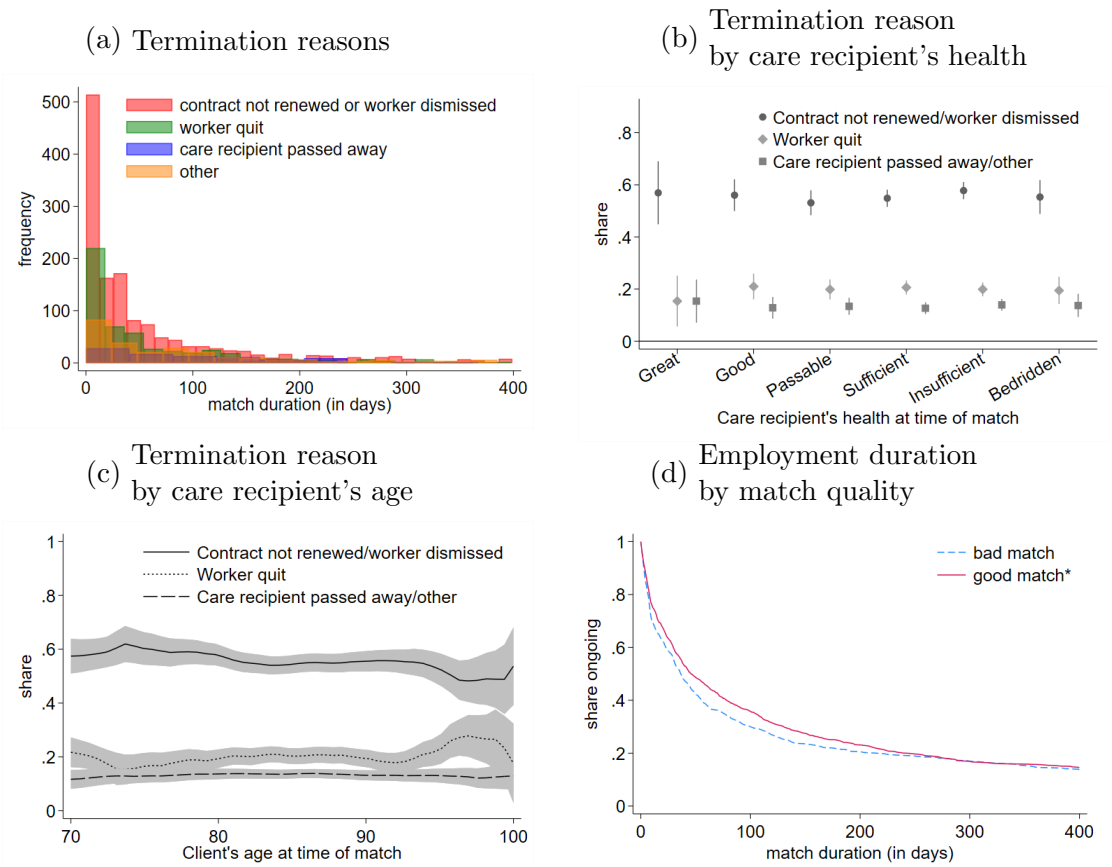
Appendix Table A8 assesses the relation between match quality (using the same measure as in Figure 2d) and employment duration also conditional on match characteristics. Correlations with employment duration are strong and very robust also to conditioning on year and province effects, as well as on client and worker characteristics and preferences, and on whether contracts are open-ended. Mismatches——whether in terms of age, gender, nationality, or health status——are associated with shorter employment relationships and higher turnover. These patterns indicate that the preferences considered here may be important for match stability. The estimated matching model presented in the next section will shed light on the causal effect of match quality on job stability.

3 Model

The model reflects the matching of elderly individuals or their families ("clients") with care workers, transfers between the two sides, as well as potential separations—with the aim of identifying the effects of preferences and match characteristics on the payoffs to both parties.[12] The framework draws on the literature on marriage

[12]While expressed preferences may reflect discriminatory attitudes rather than productivity-relevant tastes, I take them at face value as determinants of match value.

Figure 2: Separations: Termination reasons and match quality



Note: This figure shows reasons for match separations, match duration, and its relation to match quality. Panel (a) shows the distribution of job durations by reasons for contract termination. Panel (b) shows reasons for separations by the care recipient's age when the match is made. Panel (c) shows reasons for separations by the care recipient's health status. Panel (d) shows employment durations by match quality.
*Matching client preferences on worker's age, sex and origin and worker preferences on client's sex, Alzheimer and bedridden status Source: Firm administrative data.

matching (Choo and Siow, 2006; Dupuy and Galichon, 2014; Goussé et al., 2017; Chiappori, 2020; Ciscato et al., 2020; Galichon and Salanié, 2022; Gualdani and Sinha, 2023; Adda et al., 2025), where one-to-one matching has been analyzed in great depth. It builds on (Dupuy and Galichon, 2022), augmenting the marriage setting to capture that matching in the private care market reflects an employment relation. A central advantage of the care data used here is that they record explicit preferences on both sides of the market rather than merely observed attributes. Moreover, the observation of wages allows an identification of how the overall surplus generated by each match is distributed between the employing household and the worker. Finally, the availability of data on match durations, which in marriage settings typically are subject to heavy censoring, enables the identification of the

absolute level of the match surplus.

Notation. Each client i is characterized by a vector $\boldsymbol{x}_i$ (including a constant and e.g. sex or health status) as well as by a vector $\boldsymbol{p}_i^{\boldsymbol{y}}$ of preferences regarding observed worker characteristics $\boldsymbol{y}$ (such as age, origin or sex). Similarly, each worker j is characterized by $\boldsymbol{y}_j$ and a vector of preferences $\boldsymbol{p}_j^{\boldsymbol{x}}$ over the observed characteristics $\boldsymbol{x}$ of clients. Preferences may include indifference.

3.1 Match values

The flow values of matches are bi-linear as for instance also in Lindenlaub (2017) and Lindenlaub and Postel-Vinay (2023), with the difference that matching is not based on each side's characteristics only, but also their expressed preferences. For any given match with observed characteristics and preference statements $\tilde{\boldsymbol{x}}_i \equiv (\boldsymbol{x}_i' \quad \boldsymbol{p}_i^{\boldsymbol{y}\prime})'$ for client i and $\tilde{\boldsymbol{y}}_j \equiv (\boldsymbol{y}_j' \quad \boldsymbol{p}_j^{\boldsymbol{x}\prime})'$ for worker j, the expected flow value to the client is $\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j$, whereas the expected flow value to the worker is $\boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j$, where $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ are estimated parameter matrices. The payoffs are adjusted by a transfer $w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)$ that client i pays to worker j. In addition to these deterministic value components, there are match-specific factors ε_{ij} that affect client i's valuation of matching with worker j but which are unobserved to the econometrician. Similarly, unobserved factors η_{ij} contribute to worker j's valuation of matching with client i. The overall payoff to client i from a match with worker j thus is given by

$$V_{ij}^{client} \quad = \quad \tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) + \varepsilon_{ij}. \tag{1}$$

The overall payoff to worker j from a match with client i is

$$V_{ij}^{worker} \quad = \quad \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) + \eta_{ij}. \tag{2}$$

With independently Gumbel distributed[13] ε_{ij} and η_{ij} and corresponding spread parameters σ_ε and σ_η, we obtain the probability

$$\pi(j|i) = \frac{\exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\varepsilon}}{\sum_{j'} \exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_{j'} - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_{j'})\right)^{-\sigma_\varepsilon}} \tag{3}$$

[13]Identification under weaker distributional assumptions is studied by Gualdani and Sinha (2023), who show that without assumptions on the unobserved components in agents' preferences, the systematic part of the payoff function is not identified. They provide partial identification results for weaker restrictions in a matching model for the marriage market. The setup differs from the one in this paper in that transferable utility is assumed, but transfers are not observed, so that surplus allocation is not identified.

that client i's value of being matched with worker j exceeds the value of being matched with any other worker. Similarly, the probability that worker j's value of being matched with client i exceeds the value of any other match equals

$$\pi(i|j) = \frac{\exp\left(\boldsymbol{x}_i'\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\eta}}{\sum_{i'} \exp\left(\boldsymbol{x}_{i'}'\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_{i'}, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\eta}}. \tag{4}$$

Note that payoffs $\tilde{\boldsymbol{x}}_i'\boldsymbol{A}\boldsymbol{y}_j$ and $\boldsymbol{x}_i'\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_j$ must vary with characteristics of the respectively other party to not cancel in these fractions. An implication is that the vectors $\tilde{\boldsymbol{x}}_i$ and $\tilde{\boldsymbol{y}}_j$ defined above can include a constant, whereas vectors $\boldsymbol{x}_i$ and $\boldsymbol{y}_j$ cannot.

3.2 Equilibrium matching and separations

Matchmaker's objective. The matchmaking company in my setting charges a monthly fee for the duration of a contract, implying an incentive to form stable matches. Matches that do not respect preferences, instead, risk an early dissolution and clients seeking alternative care arrangements.

Separation. I assume that matches dissolve with hazard rates that are inversely proportional to the flow value of the match, with a proportionality factor δ (see the specification of the likelihood function in Appendix H). This reflects the idea that better matches are more stable. Linking separations to the full match surplus rather than the separate payoffs to clients and workers is consistent with the assumption of transferable utility if in case of an adverse separation shock transfers can adjust.

Equilibrium. Under the above assumption, the matchmaker's objective of maximizing aggregate match durations is achieved by maximizing the aggregate surplus. As shown by Galichon and Salanié (2022), the aggregate surplus in turn is maximized by the decentralized matching equilibrium. Focusing on the later, one can apply Bayes' rule to equations (3) and (4) to obtain in both cases the match probability for a pair (i, j):

$$\begin{aligned} \pi(i,j) &= \frac{\exp\left(\tilde{\boldsymbol{x}}_i'\boldsymbol{A}\boldsymbol{y}_j - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\varepsilon}}{\sum_{j'} \exp\left(\tilde{\boldsymbol{x}}_i'\boldsymbol{A}\boldsymbol{y}_{j'} - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_{j'})\right)^{-\sigma_\varepsilon}} f(i) \\ &= \exp\left(\tilde{\boldsymbol{x}}_i'\boldsymbol{A}\boldsymbol{y}_j - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) - a(\tilde{\boldsymbol{x}}_i)\right)^{-\sigma_\varepsilon}, \end{aligned} \tag{5}$$

where $a(\tilde{\boldsymbol{x}}_i) = \log \sum_{j'} \exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_{j'} - w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_{j'})\right)^{-\sigma_\varepsilon} - \sigma_\varepsilon \log f(i)$ and $f(i)$ denotes the empirical probability distribution of clients. Similarly,

$$\begin{aligned} \pi(i,j) &= \frac{\exp\left(\boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\eta}}{\sum_{i'} \exp\left(\boldsymbol{x}_{i'}' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_{i'}, \tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\eta}} g(j) \\ &= \exp\left(\boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) - b(\tilde{\boldsymbol{y}}_j)\right)^{-\sigma_\eta}, \end{aligned} \tag{6}$$

with $b(\tilde{\boldsymbol{y}}_j) = \log \sum_{i'} \exp\left(\boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_{j'})\right)^{-\sigma_\eta} - \sigma_\eta \log g(j)$ and empirical probability distribution $g(j)$ of workers.

Equating (5) and (6) and rearranging yields the equilibrium match probability for client i and worker j

$$\pi(i,j) = \exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j + \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j - a(\tilde{\boldsymbol{x}}_i) - b(\tilde{\boldsymbol{y}}_j)\right)^{-(\sigma_\varepsilon + \sigma_\eta)}, \tag{7}$$

where $a(\tilde{\boldsymbol{x}}_i)$ and $b(\tilde{\boldsymbol{y}}_j)$ capture the expected value of alternative matches to the client and the worker, respectively. With N matched pairs of clients and workers, each client has a mass $f(i) = 1/N$ and each worker a mass $g(j) = 1/N$. It follows that $a(\tilde{\boldsymbol{x}}_i)$ and $b(\tilde{\boldsymbol{y}}_j)$ are uniquely determined (up to a constant) by the system[14]

$$\sum_{j=1}^{N} \exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j + \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j - a(\tilde{\boldsymbol{x}}_i) - b(\tilde{\boldsymbol{y}}_j)\right)^{-(\sigma_\varepsilon + \sigma_\eta)} = 1/N, \quad \forall i = 1, ..., N, \tag{8}$$

$$\sum_{i=1}^{N} \exp\left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j + \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j - a(\tilde{\boldsymbol{x}}_i) - b(\tilde{\boldsymbol{y}}_j)\right)^{-(\sigma_\varepsilon + \sigma_\eta)} = 1/N, \quad \forall j = 1, ..., N. \tag{9}$$

3.3 Surplus identification

Conditional on $a(\tilde{\boldsymbol{x}}_i)$ and $b(\tilde{\boldsymbol{y}}_j)$, equation (7) maps the probability that agents with preferences and characteristics $(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)$ form a match to payoff parameters $\boldsymbol{A} + \boldsymbol{\Gamma}$. However, in data that cover matches only, match probabilities must sum to one. Such data thus lack one degree of freedom and only can identify *relative* payoffs of matches with different observed combinations of characteristics. This implies that a normalization on the level of the surplus is required. On the upside, the logit structure of unobserved heterogeneity implies that the odds ratios of observed matches do not depend on the characteristics of unmatched agents. Accordingly,

[14] Up to a normalization of the level of match values, the equilibrium thus is unique. In the full likelihood estimation detailed below, the level of values will in fact be identified by the part of the likelihood function that captures the hazard of separation as a function match values.

the estimation of parameters capturing payoff *changes* between different potential matches do not require information on unmatched agents, but only relative match frequencies. Linking relative match frequencies to relative match durations also identifies the proportionality factor δ.

Given δ, absolute match durations then identify the surplus *level*. This avoids resorting to an arbitrary level normalization. Moreover, observed separations by agents' characteristics identify heterogeneity in the surplus level, as explained below.

Note that equations (7)-(9) could be rewritten in terms of $\boldsymbol{A} + \boldsymbol{\Gamma}$, implying that the distribution of matches across types characterizing agents i and j alone cannot separately identify the payoffs to the two sides. As explained in Section 3.4, separate identification of the parameter matrices $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$, however, is feasible with information on transfers between clients and workers. This is important conceptually, because match characteristics may be valued differently by the two sides. For instance, assortative matching on sex may be differently important to care givers and care recipients.

Since in clients' choice probabilities (3) any payoff components that do not vary across workers j cancel from the fraction, their contribution to the client payoff is not identified. The same holds true for workers' choice probabilities (4) and terms that do not vary across clients i. That is, relative match frequencies and wages identify variation in *clients'* payoff by worker characteristics, but they do not identify variation in *workers'* payoff by worker characteristics; vice versa for client characteristics. This variation in payoffs by agents' own characteristics instead is again facilitated by variation in the separation rates across observed client and worker types.

In sum, by jointly exploiting information from observed matches, contractual wages (explained below), and separations, the model identifies all the parameters in the above expressions, which are crucial for understanding the welfare implications of meeting individual preferences in the private care market.

3.4 Equilibrium transfers and observed wages

Solving (5)-(6) for $w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)$ yields the equilibrium transfer

$$w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) = \frac{\sigma_\eta}{\sigma_\varepsilon + \sigma_\eta} \left(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j - a(\tilde{\boldsymbol{x}}_i)\right) + \frac{\sigma_\varepsilon}{\sigma_\varepsilon + \sigma_\eta} \left(b(\tilde{\boldsymbol{y}}_j) - \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j\right)$$

for matches with preferences and characteristics $\tilde{\boldsymbol{x}}_i$ of employing households and $\tilde{\boldsymbol{y}}_j$ of care workers. These transfers increase (decrease) with the payoff to clients (workers) and the expected value of alternative matches to workers (clients). Moreover, they reflect the relative importance of unobserved factors. Two remarks are in order: First, since the systematic parts $\tilde{\boldsymbol{x}}_i'\boldsymbol{A}\boldsymbol{y}_j$ and $\boldsymbol{x}_i'\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_j$ of each side's payoff are the surplus relative to not being matched, they also capture variation in outside options (identified from different separation rates). This links equilibrium transfers to the outside options of clients and workers. Better labor market prospects outside the care sector for workers with certain characteristics, for instance, imply a lower surplus $\boldsymbol{x}_i'\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_j$ from working in elderly care (relative to the best expected alternative) and rationalize a higher transfer. Second, while w depends on the distributions of ε_{ij} and η_{ij}, it does not depend on the match-specific realization of these components. This mirrors well the context analyzed here, where the match-making company negotiates a wage with clients and workers separately, based on their characteristics and preferences, but without revealing the identity of the respectively other side (and thus potentially unobserved factors). Note that since these are private employment contracts between households and care workers, there are no fixed wage schedules.

I observe contractual wages W_{ij} in the data, displayed in Panel (a) of Figure 3. Contractual wages are bounded from below due to collective bargaining agreements. The median wage in the data is 5.85 euros per hour, with a mean of 6.10 euros. Panel (b) presents weekly hours stated in the contract, with bunching at the legal maximum of 54 hours per week.

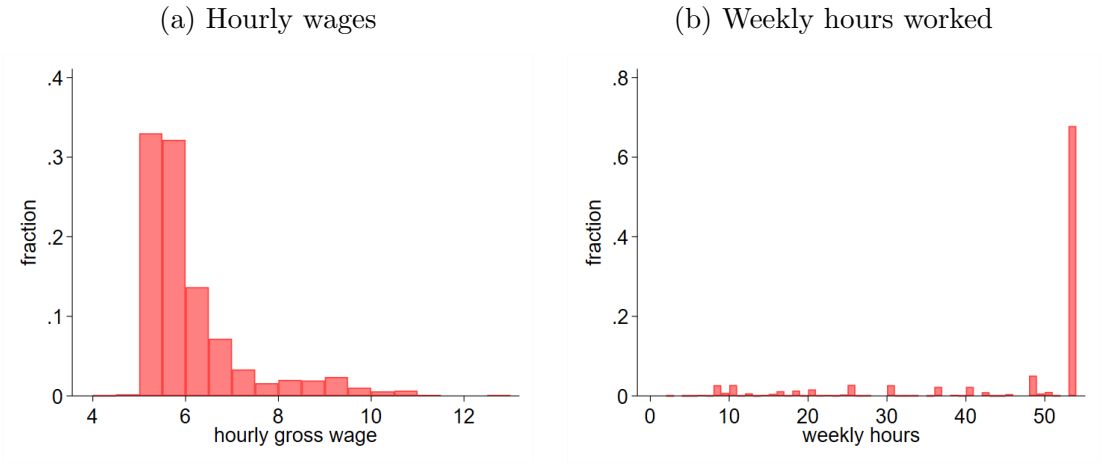
A discrepancy between observed contractual wages and true transfers may arise if work hours exceed the contractual number of hours used to calculate hourly wages or if part of the compensation is in-kind. I thus allow for observed wages W_{ij} to be an imperfect measure of the true transfers $w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)$, such that

$$W_{ij} \quad = \quad \alpha + w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j) + \omega_{ij}, \tag{10}$$

with potential shifter α and normally distributed measurement error $\omega_{ij} \sim \mathcal{N}(0, \sigma_\omega^2)$.

Equation (10) will be part of the likelihood function to separately identify the payoff matrices $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ contained in $w(\tilde{\boldsymbol{x}}_i, \tilde{\boldsymbol{y}}_j)$. For illustration, suppose that the sorting on care recipients' and care workers' own sex suggests a relatively high overall surplus of matching male caregivers with male care recipients, identifying a positive value for the corresponding element in the joint surplus matrix $\boldsymbol{A} + \boldsymbol{\Gamma}$. Additionally observing a higher wage for such matches (compared to matches

Figure 3: Distributions of weekly hours worked and hourly wages



Note: This figure illustrates the distribution of hourly wages (Panel (a)) and weekly contractual hours (Panel (b)). Source: Firm administrative data.

where either individual is female) implies that a larger share of the gain from matching men with men is allocated clients.

3.5 Estimation

The model is estimated iteratively using match characteristics, wage observations, and job separations. The parameters to be estimated include preference parameters $\{\boldsymbol{A}, \boldsymbol{\Gamma}, \sigma_\varepsilon, \sigma_\eta\}$, wage function parameters $\{\alpha, \sigma_\omega\}$ and the hazard factor δ that governs match dissolution conditional on match values. All parameters are estimated jointly as follows.

First, conditional on an initial guess for $\boldsymbol{A}$, $\boldsymbol{\Gamma}$, σ_ε and σ_η, the values of $a(\tilde{\boldsymbol{x}}_i)$ and $b(\tilde{\boldsymbol{y}}_j)$ are retrieved by iterating over equations (8) and (9).

Second, to recover the wage function parameters, observed contractual wages W_{ij} are regressed on $(\tilde{\boldsymbol{x}}_i' \boldsymbol{A} \boldsymbol{y}_j - a(\tilde{\boldsymbol{x}}_i))$ and $(b(\tilde{\boldsymbol{y}}_j) - \boldsymbol{x}_i' \boldsymbol{\Gamma} \tilde{\boldsymbol{y}}_j)$.[15] Based on (10), this regression yields estimates for the shift parameter α and for the ratios $\sigma_\eta/(\sigma_\varepsilon + \sigma_\eta)$ and $\sigma_\varepsilon/(\sigma_\varepsilon + \sigma_\eta)$, while its residual variance provides an estimate of σ_ω^2.[16]

Third, I construct the likelihood function that encompasses match formation,

[15] In practice, I first take out province-level variation, by first regressing hourly wages on province indicators and then adding residuals to the mean hourly wage.

[16] The R-square from this regression is 0.052, which is remarkably high for an wage equation with only three free parameters. For comparison, a regression of wages on an intercept, an indicator for the worker's sex and linear age (also 3 parameters) yields an R-square of less than 0.003. Including indicators for the worker's sex and European origin, as well as a full set of age indicators (57 parameters) raises the R-square to only 0.032.

wage observation, and match separation (see Appendix H). This joint likelihood is maximized with respect to the parameters δ, $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$, generating new guesses for these parameters. This three-step procedure is iterated until convergence. Note that the likelihood is a function of all parameters, including also $\sigma_\varepsilon, \sigma_\eta, \alpha$ and σ_ω. I can thus in a last step maximize the likelihood function over all parameters,[17] which is slower than the OLS regression in the second step but yields efficient estimates. I then calculate asymptotic standard errors through the joint information matrix of all parameters to avoid inefficient two-step procedures.

4 Results

The estimated parameters provide insight into how clients and workers value different attributes in the private care market and how these valuations translate into job stability.

4.1 Client valuations

Table 3 reports the estimated payoff matrix $\boldsymbol{A}$ for clients, while Table 4 below shows the corresponding parameters in $\boldsymbol{\Gamma}$ for workers. To focus on preferences and to limit the number of parameters that need estimation, $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ are constrained such that an agent's payoff depends on whether their own preferences are met by the other party's corresponding characteristic. In addition, both matrices include full interactions between the two sides' characteristics. For each preference dimension reported in the upper part of Table 3, indifference is the omitted category.

The estimated client valuations in Table 3 confirm that on average clients derive a higher surplus from matching with a worker whose characteristics align with their preferences regarding the worker's age, sex, and origin. The largest penalty, 64 cents per hour, occurs when clients who expressed a preference for female caregivers are matched with a male worker. This is sizable, in particular compared to a median wage of 5.85 euros/hour.

The baseline coefficients for worker characteristics (last row of Table 3) indicate that for clients who are indifferent (the omitted preference category), being matched with a young or male worker yields a higher surplus than being matched with a female worker aged 40-60. These gains, however, are eroded for the sizable

[17] Note also that $a(\tilde{\boldsymbol{x}}_{i_m})$ and $b(\tilde{\boldsymbol{y}}_{j_m})$ do not involve separate parameters, but are pinned down exactly (up to a constant) by the system (8)-(9).

Table 3: Client valuations (Payoff parameters in $\boldsymbol{A}$)

	Young worker	Male worker	Non-European worker
Client Preferences			
Client prefers younger worker	0.123		
	(0.000)		
Client prefers older worker	-0.087		
	(0.004)		
Client prefers female worker		-0.638	
		(0.007)	
Client prefers male worker		0.254	
		(0.014)	
Client prefers European worker			-0.145
			(0.016)
Client prefers non-European worker			0.130
			(0.017)

	Young worker	Male worker	Non-European worker	Baseline effect
Patient Characteristics				
Patient is male	-0.175	0.318	-0.021	0.223
	(0.004)	(0.026)	(0.013)	(0.020)
Patient is bedridden	0.028	-0.244	0.012	-3.210
	(0.004)	(0.030)	(0.014)	(0.033)
Patient has Alzheimer	-0.000	0.189	-0.000	0.937
	(0.004)	(0.017)	(0.017)	(0.083)
Baseline effect	0.065	0.107	-0.029	
	(0.015)	(0.014)	(0.011)	

Note: This table presents the estimated payoff matrix $\boldsymbol{A}$, capturing client valuations for different match characteristics, denoted in euros/hour. Clients' indifference over workers' age, sex and origin are omitted categories, as are workers being aged 40-60, female or European, and care recipients being female, not bedridden and without Alzheimer's. Asymptotic standard errors are reported in parentheses.

share of clients who explicitly prefer older or female workers. Baseline productivity of non-European workers is slightly lower than for European workers. In addition, clients who expressed a preference for European workers suffer a 15 cents per hour loss if they are matched with a non-European worker, with a slightly weaker penalty for the opposite mismatch. Preferences thus significantly shape the subjective quality of a match.

The lower part of Table 3 captures the full interaction between care recipient and worker characteristics. These interactions largely act as controls. To demonstrate that including preferences in the payoff matrices above and beyond complementarities between agents' characteristics is fundamental, I re-estimate a restricted model that assumes clients and workers are matched exclusively on own characteristics (equivalent to setting the upper parts of Tables 3 and 4 to zero).

The resulting estimates are displayed in Appendix Table A10. They show that such a restricted model falsely suggests much larger values of assortative matching on sex, inflating the corresponding estimate by a factor of almost two, while masking the higher payoff generated by male workers in the data who are matched with indifferent clients.

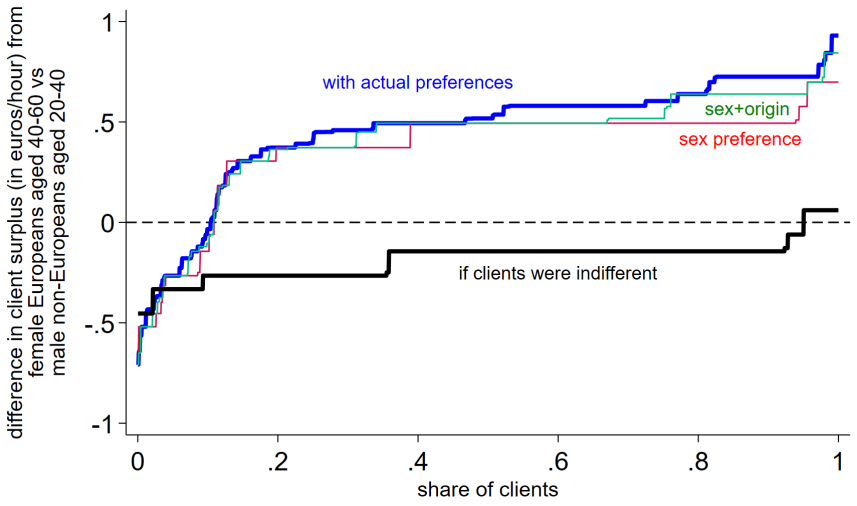
To illustrate the importance of preferences, Figure 4 shows variation in client valuations depending on worker characteristics and different preference scenarios. The figure displays the difference between the estimated payoff to clients when matched with a female European worker aged 40–60 (the most frequently demanded set of attributes) versus a male non-European worker aged 20–40. The blue line depicts this difference for the actual distribution of client preferences in the data. It shows that for a majority of 90 percent of clients, the former type of worker generates a higher payoff, equal to 52 cents/hour for the median client. For comparison, the black line represents the hypothetical case in which clients are indifferent about worker attributes. In that case, younger male non-European workers actually generate a higher payoff to clients than their older female European counterparts. This higher payoff is driven by a higher surplus generated by young and male care workers if client are indifferent about a worker's age and gender (see the last row in Table 3). The difference between the blue and the black lines hence can be attributed to client preferences. The red line re-introduces client preferences over a worker's sex, showing that these bridge the largest part of the gap. The green line adds origin preferences, with the remaining gap deriving from client preferences over a worker's age.

Parameter estimates in the last column of Table 3 indicate how the value of matches varies relative to the best alternative if a client is not matched with a worker and, say, relies on informal care by family members or nursing home care. These values are identified from modeling match separations, whereas all other parameters are identified from relative match frequencies and wages. They indicate that match values are particularly high for care recipients diagnosed with Alzheimer's disease, whereas they are reduced for bedridden patients, for whom institutional care may generate a relatively higher value than it does for care recipients in better health.

The baseline level for the total surplus is estimated to be $V_0 = 14.60$ euros per hour (listed in Appendix Table I), pertaining to the omitted types of clients and workers.[18] Again, this surplus level is identified from separations. Assuming

[18]The omitted client types are female clients without Alzheimer's who are not bedridden and who are indifferent about worker characteristics. The omitted worker types are female

Figure 4: Client payoffs by worker type and preference type



Note: The figure shows the distribution of the difference in client payoffs (in euros/hour) when matched with a female European worker aged 40-60 versus a male non-European worker aged 20-40. The blue line represents client payoffs under different preference scenarios: a counterfactual scenario where clients are indifferent to all three attributes (black); accounting for preferences over workers' sex as in the data (red); accounting for preferences over workers' sex and origin (green); and actual preferences over workers' age, sex and origin (blue). Positive values indicate higher surplus from the female European worker. Source: Firm administrative data and model estimates.

that the surplus shares net of wages are inversely proportional to the relative probabilities that either side terminates the match lets me determine also the distribution of this payoff between clients and workers. Given relative match termination probabilities by the two sides, I estimate that about two thirds of the match surplus goes to workers. Appendix I further explains the procedure and Figure A11 shows the estimated distributions of client payoffs derived from different types of workers.

4.2 Worker valuations

For the worker side, Table 4 displays the estimated payoff matrix $\mathbf{\Gamma}$. The estimates show that meeting caregivers' stated preferences regarding patient characteristics also translates into higher surplus—albeit their payoff responds less strongly than that of clients to mismatches.

Most workers report an availability to work with either female or male patients. Among those who do not, workers who prefer female (male) patients experience

Europeans aged 40-60 who are available for work with patients of either sex and who do not state an availability for working with Alzheimer's or bedridden patients.

Table 4: Worker valuations (Payoff parameters in $\mathbf{\Gamma}$)

	Male patient	Bedridden patient	Alzheimer patient	
Worker Preferences				
Worker prefers female patients	-0.208			
	(0.024)			
Worker prefers male patients	0.167			
	(0.020)			
Worker available for bedridden patients		0.004		
		(0.012)		
Worker available for Alzheimer patients			0.061	
			(0.015)	
	Male patient	Bedridden patient	Alzheimer patient	Baseline effect
Worker Characteristics				
Worker is young	0.117	-0.040	-0.006	-0.066
	(0.018)	(0.019)	(0.015)	(0.027)
Worker is male	0.046	0.008	-0.093	-0.071
	(0.016)	(0.016)	(0.018)	(0.024)
Worker non-European	0.001	-0.038	0.049	-0.000
	(0.014)	(0.023)	(0.024)	(0.018)
Baseline effect	-0.227	-0.898	-0.031	
	(0.016)	(0.012)	(0.015)	

Note: The table presents the estimated payoff matrix $\mathbf{\Gamma}$ capturing worker valuations for different match characteristics, denoted in euros/hour. Workers' indifference over patients' sex is an omitted category, as is workers' inavailability for patients with Alzheimer's disease or bedridden patients, care recipients being female, not bedridden and without Alzheimer's, and workers being aged 40-60, female and European. Asymptotic standard errors are reported in parentheses.

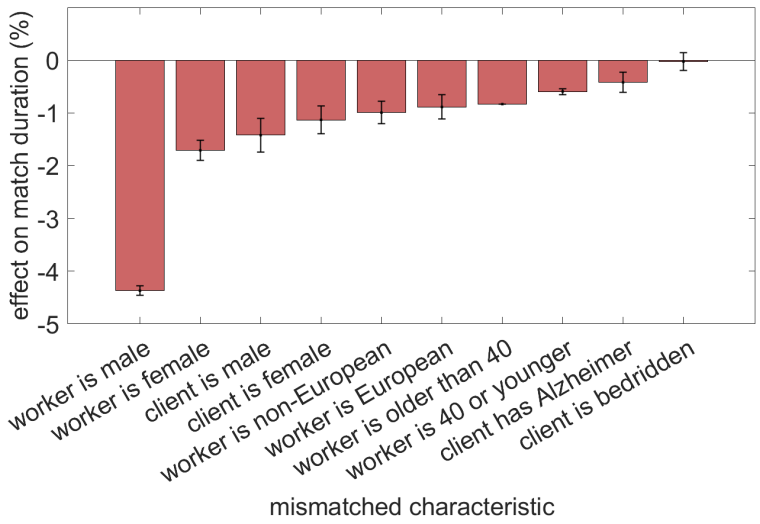
a penalty of 21 cents (17 cents) per hour when assigned to men (women). While this is still sizable compared to the median wage of 5.85 euros, it is smaller than the corresponding loss to clients demanding a female carer (reported in Table 3). These results underscore that preferences operate—albeit asymmetrically—on both sides of the market.

As in Table 3, the bottom part of Table 4 captures the full interaction between care recipient and worker characteristics. Being matched with a bedridden patient implies a loss of 90 cents per hour (see the last row of Table 4). Statistically, this loss does not vary with caregivers' stated availability. Working with Alzheimer's patients entails a loss mostly for male workers. The last column of the table is again identified from variation in match separations and indicates relatively better outside options for young and male care workers. All remaining model parameters are listed in Appendix Table I.

4.3 Match duration

Taken together, these results confirm that preferences significantly affect match quality and surplus. They also invite two related questions. First, what are the effects of preferences on turnover? The estimated structural model with separations facilitates a causal evaluation of the effects preference violations have on employment stability in private home care—a sector that is characterized by exceptionally high turnover. Figure 5 visualizes the magnitudes of these effects, which represent the causal counterpart to the descriptive associations shown in Figure 2d and Appendix Table A8. The figure shows that violating care recipients' or workers' preferences over the other side's sex shortens employment durations by between 1.1 and 4.4 percent. Matches that violate the client's preference over a worker's origin are shortened by about 1 percent.

Figure 5: Effect of mismatch on match duration (%)



Note: Bars show the estimated percentage changes in match duration due to different preference violations. Vertical lines and whiskers indicate 95% confidence intervals. Source: Estimates of changes in match duration from the model using company administrative data.

A second set of broader questions that arise pertains to (I) aggregate welfare in this important market, (II) how welfare depends on changes in available worker types, (III) which parts of the elderly population will grow in the near future, (IV) which preferences this growth is associated with, (V) the growth in market volume to be expected. Since preferences are unevenly distributed, changes in the composition of elderly populations may shift future client preferences. The next section exploits register data to examine this question.

5 Outlook from current population registers

I use register panel data by municipality, sex, and age[19] to project elderly populations forward and assess the future demand for elderly care. For this, I first compute the geometric mean of survival rates during the last five years prior to the pandemic (2015–2019) for each municipality-sex-age cell (approximately 1.5 million non-empty cells). Note that "survival" rates can be larger than one, accounting for population growth due to migration. Second, I apply these survival rates to predict population changes for each cell from 2022 to 2040. I choose to not project further into future, since an implicit assumption in this projection is that mortality and migration rates are as during the 2015-2019 period. For most of this section, I focus on the evolution of the adult population share aged 80 and older, as this group drives the demand for long-term care.[20]

5.1 Demographic predictions

Figure 6 visualizes the predictions. Panel (a) displays the age distribution of the population aged 60 and above by sex in 2022 as well as the corresponding predictions for 2040. The figure shows the stark demographic transition to be expected in Italy, with increases in the retirement age population, but predicted decreases among younger ages.[21] Although the number of women in the elderly population continues to clearly exceed the number of men, the figure also reveals a decline in that difference. Panel (b) visualizes this more clearly, separately for register data in 2000, 2022, and the prediction for 2040. The lower share of women among individuals in their 60s and 70s in 2022 compared to 2000 predicts a smaller female share among individuals in their 80s and 90s in 2040 compared to 2022.

Panels (c) and (d) of Figure 6 plot for each municipality the percentage point increase in the share of 80+ old resident against population sizes (on a log scale), with population size also indicated by marker area. Panel (c) shows that smaller and midsized municipalities are expected to experience the largest increases in their elderly population shares. In the smallest municipalities (up to 1,000 residents), the share of 80+ individuals is projected to grow by 4.8 percentage points,

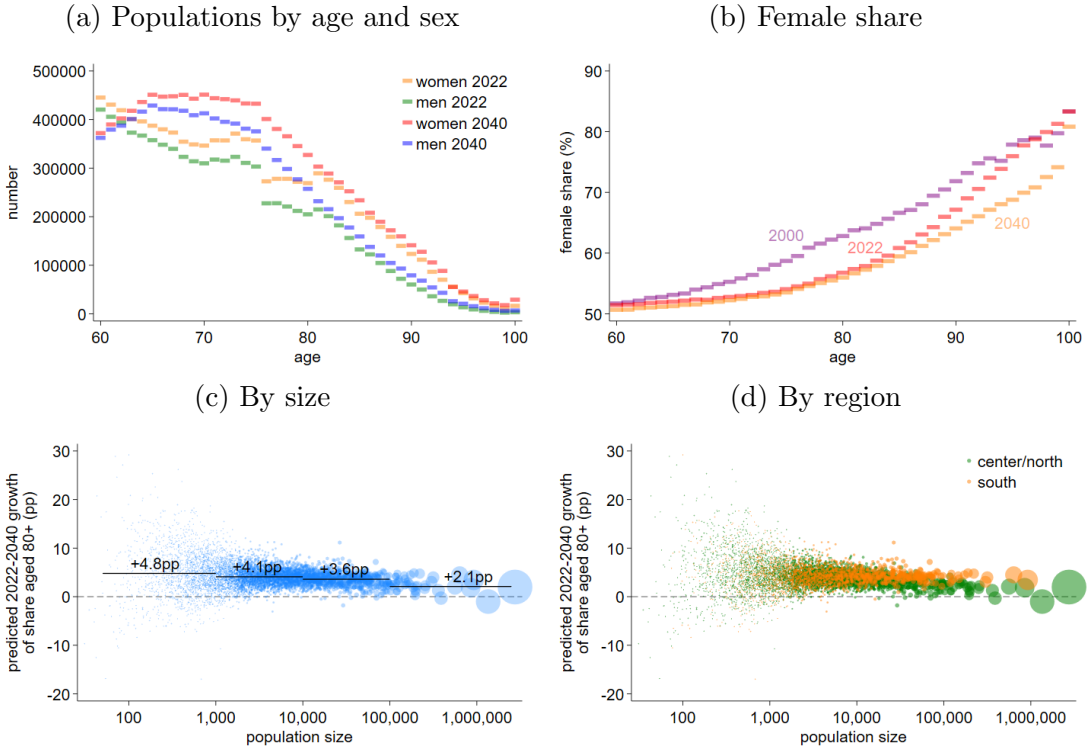
[19] These data are publicly available through https://esploradati.istat.it.

[20] Patterns are qualitatively identical when considering percentage changes in local populations aged 80 and older. I focus on percentage point changes in elderly population shares to capture the changes in potential demand for elderly care relative to the working-age population who may provide part of these care services.

[21] The lower numbers at ages 76-80 result from lower (live) births during the late years of the Second World War.

compared to just 2.1 percentage points in large cities with more than 100,000 residents. The Panel (d) adds a regional dimension, revealing that these demographic shifts are particularly pronounced in the south, where municipalities are expected to see a disproportionate rise in the elderly population.[22] This suggests that future demand for elderly care services will increasingly be concentrated in these areas.

Figure 6: Projected growth in the 80+ population.



Note: Panel (a) displays age distributions by sex in 2022 and the predictions for 2040. Panel (b) shows the decrease in the share of women within each age in register data for the years 2000 and 2022, as well as the prediction for 2040. Panel (c) shows the projected growth in the adult population share aged 80 and older between 2022 and 2040 across municipalities of different sizes. Panel (d) further differentiates these projections by region, highlighting differences between southern and central/northern Italian municipalities. Dot areas in Panels (c) and (d) are proportional to total population. Source: Own computation based on ISTAT municipal population register data 2015-2022.

[22] While differences in elderly population share changes could be explained by the emigration of younger individuals, Appendix Figure A12 provides evidence against this as the sole explanation, at least for municipalities upward of 10,000 residents. Panel (a) of that figure shows that the elderly population grows most strongly in mid-sized municipalities, whereas growth declines for municipalities with more than 10,000 residents. Appendix Figure A12b reveals the same north-south divide as in Figure 6d also in the percentage growth of absolute 80+ population sizes.

5.2 Merging with preference data

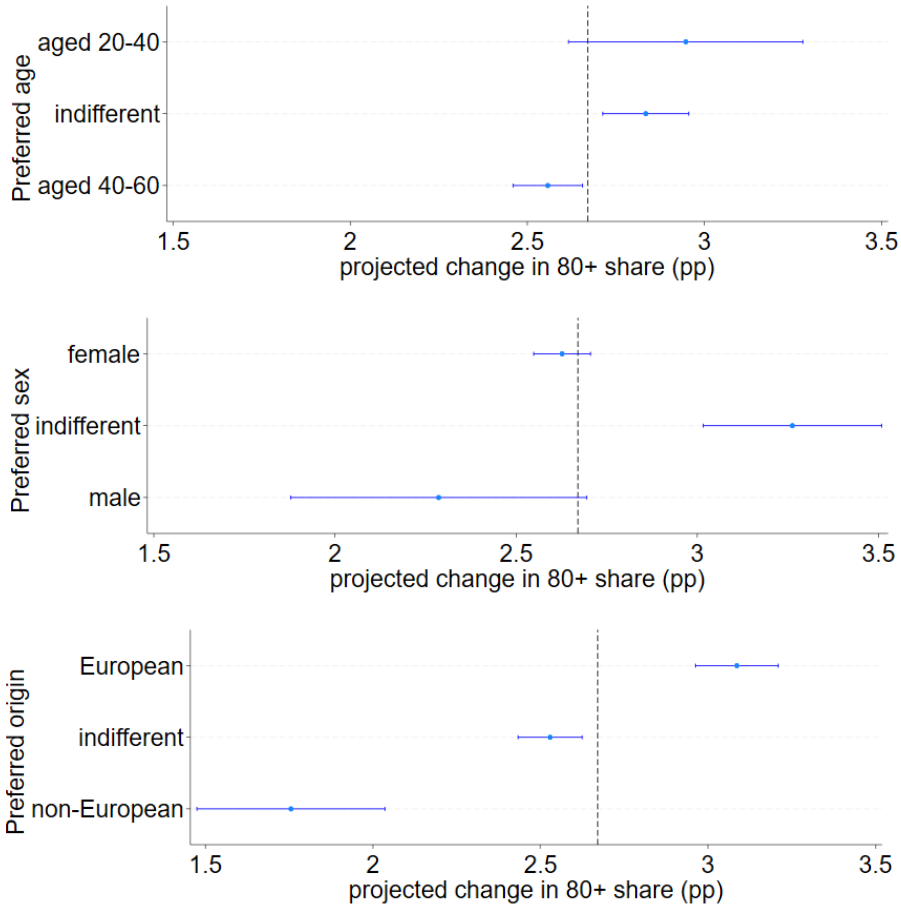
To understand how these demographic changes interact with preferences, I merge the projections with clients in the company data based on their municipality, sex and age. This allows me to assess the relation between predicted elderly population growth and preferences. If the distribution of preferences remains stable over time (at least over the relatively short horizon I consider), shifts in the population structure will influence the types of workers that are in higher demand. While my cross-sectional firm data do not allow me to evaluate preference changes over time, I can assess their stability across municipalities with different population compositions. Specifically, I consider whether clients are less likely to demand older, female or European care workers when they reside in municipalities with higher male or foreign population shares, or where the share of the 20-40 among all 20-60 year old residents is larger. Appendix Figure A13 shows that this is not the case.

Figure 7 visualizes how predicted 80+ population shares are related to client preferences for worker characteristics. Although the company has clients all over the country, northern Italian municipalities are overrepresented. Mean growth in the adult population share aged 80 and older for the demographics in the company data, indicated by the vertical dashed lines, hence is lower than the country average.

The top panel shows how predicted growth in the 80+ population share varies across clients with different preferences over a caregiver's age. The middle and bottom panels depict projected changes by preferences over workers' sex and origin, respectively. The first two panels indicate an slight erosion of the bias towards middle-aged care workers and more flexibility regarding care workers' gender. These derive from a relatively stronger increase in men and in relatively younger individuals among the elderly population, see also Figure 6a. Appendix Figure A16 indicates a correlation between care recipients' and preferred caregivers' age, whereas Appendix Figure A17 shows that male care recipients are more likely indifferent about a care worker's gender.

The strongest trend is apparent for origin preferences, with disproportionate growth in elderly population shares among demographics more likely to prefer European caregivers (Figure 7a). Figure 8 shows that this is driven by clients in smaller and southern Italian municipalities, which are predicted to grow most strongly, more often expressing a preference for European care workers.

Figure 7: Projected change in 80+ share by client preference over workers' age (top), origin (middle), and sex (bottom).

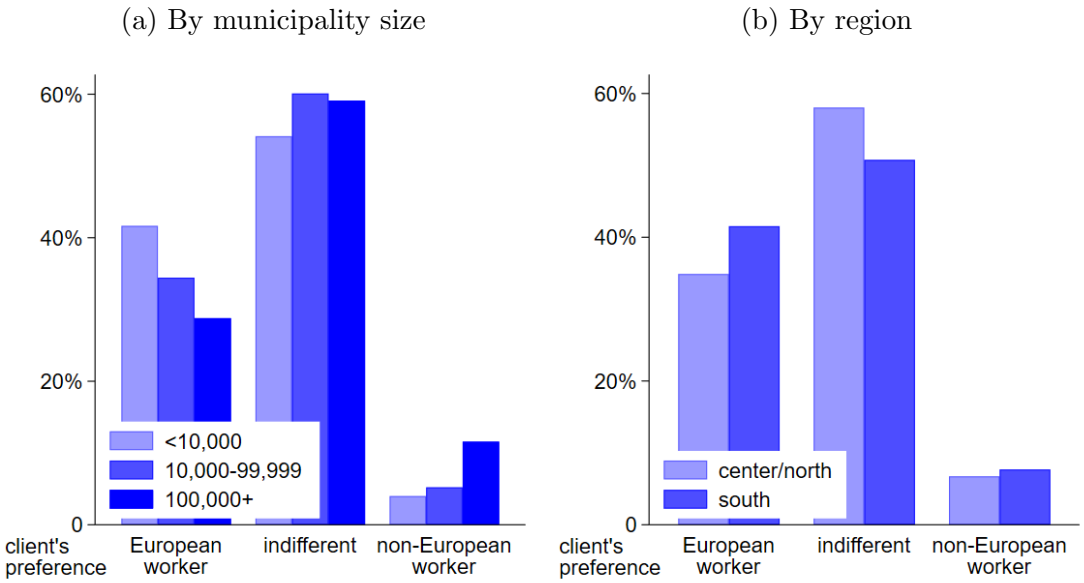


Note: The figure presents projected changes in the share of the population aged 80 and older between 2022 and 2040, disaggregated by client preferences over workers' age (top), origin (middle), and sex (bottom). These projections are based on demographic shifts in the elderly population and assume persistence in the distribution of preferences over time. Source: ISTAT municipal population register data, firm data on client preferences.

5.3 Market volume and welfare

Aggregation. Given the rapid growth of elderly populations, long-term care is a major sector in many economies. The detailed information on care contracts in my data allow an approximation of the market volume. To this end, I scale company data and model estimates using the full population registers by municipality, sex, and age, as well as the reliance on private home care reported in SHARE data. First, I match clients from the company data to the register data by municipality, sex and age, and scale them using the population size in the

Figure 8: Client preferences for worker origin by municipality size and by region.



Note: The figure shows client preferences for caregivers' origin for different locations. Panel (a) shows the distribution of preferences by municipality size, Panel (b) presents preferences by region. Source: ISTAT municipal population register data, firm administrative data.

respective municipality-sex-age cell.[23] Second, since not all elderly individuals require care services, I use SHARE data to calculate the fraction of respondents in each age-sex cell who report the use of paid care services at home.[24] I then scale populations down by the predicted shares.

Market volume. Multiplying monthly gross salaries recorded in the company data by 12 and scaling them as explained above yields a potential market volume of 3.7 billion euros in 2022. Given that paid home care services reported in the SHARE data include unregistered work, where pay may differ from the salaries reported in the company data, this is an imperfect measure. Yet, it can serve as a plausibility check in comparison to other (equally imperfect) estimates in the literature. Specifically, my approximation of market volume is comparable to the 4.6 billion euros reported by Brugiavini et al. (2025), who include other domestic tasks and services such as meals-on-wheels in their calculation. My estimate amounts to

[23]The population in municipality-sex-age cells without observations in the company data is allocated evenly among the remaining cells.

[24]SHARE data do not contain municipality identifiers. To cover all age-sex cells, I use predicted shares based on a probit regression of an indicator for using paid home care services on age and sex.

0.19 percent of Italy's gross domestic product of 2 trillion euros in 2022, a similar fraction to the 0.15 percent of GDP estimated by Geyer et al. (2025) for Germany, but higher than estimates for countries with younger populations, such as England (Banks et al., 2025) or the U.S. (Gruber and McGarry, 2023). Applying the predicted growth in elderly populations of Section 5.1 suggests an increase to 4.5 billion euros by 2040.

Aggregate welfare under different worker compositions. Observed payments reflect only part of the welfare generated for care receiving households. The model and client payoffs estimated in this paper, instead, inform about the willingness to pay—and thus the overall suplus—for this particular type of care service. Moreover, the estimated payoff matrix $\boldsymbol{A}$ facilitates a computation of care recipient welfare under an ideal worker pool versus the welfare achieved when the composition of workers is biased towards certain types. This is a timely issue, as some of the main origin countries of care workers from eastern Europe face strongly aging populations on their own. Accordingly, the supply of workers from these countries can be expected to decline, raising the need for western European countries to attract immigrant workers from non-European origins.

Applying the same scaling exercise as for market volume, but using the payoffs estimated from the model, yields an aggregate annual surplus to clients of 6.7 billion euros under an optimal worker pool. This number would increase to 8.1 billion euros by 2040. For comparison, if care workers were exclusively of non-European origin, but still with an optimal composition in terms of age and sex, the aggregate client surplus in 2040 would fall by 0.7 percent to 8.0 billion euros. This small loss stands in stark contrast to the 34 percent of company clients stating a preference for European workers, a share that is predicted to increase further given the demographic change outlined above. The relative welfare loss from shifting to non-European care workers thus would likely be modest, in particular when measured against the large aggregate surplus generated by this sector relative to agents' next best alternatives to which the estimated surplus compares.

6 Conclusion

This paper draws on internal company data that provide unique information on stated preferences and matching between elderly care recipients and private care workers. While the data provide novel insights into preferences in this important domain, a conceptually distinct question is whether these preferences matter

quantitatively. Through the lens of a matching model, I estimate match values as functions of either party's preferences over characteristics of the respectively other side, including age, sex, origin, and health conditions, as well as the effects preference violations can have for employment stability. The results reveal substantial penalties for mismatches, including a reduction in surplus of up to 11 percent of the median wage when clients prefer a female worker but are matched with a male caregiver. Such a mismatch reduces expected employment duration by more than 4 percent. Compared to clients who are indifferent about a worker's origin, clients preferring European workers experience a loss equal to 2.5 percent the median wage when matched with a non-European worker.

Overall, this study underscores the importance of accounting for explicit preferences. While my data cover a specific segment of the market for long-term care, future research might build on the findings presented here by investigating how policy interventions, labor mobility, and technological changes could affect matches in a broader dynamic equilibrium framework that captures the choice of care modes and the sector choice of potential care workers.

Using municipal-level population registers by demographic groups, I project the evolution of elderly populations and find that the female share among the elderly is in decline. As demographic trends continue to reshape demand in the private care sector, the results from this study suggest benefits from attracting more men into this female dominated sector. Moreover, the predictions highlight that the elderly population share is expected to increase most rapidly in smaller and southern Italian municipalities. Company clients in these areas more often express a preference for European care workers. Aging trends in care workers' Eastern European countries of origin, however, imply that future recruitment may have to shift towards non-Europeans. I estimate that aggregate welfare of care recipients in case care workers were exclusively of non-European origin would fall by a mere 0.7 percent compared to an optimal composition of the worker pool. This is in stark contrast to the more than one third of company clients stating a preference for European care workers and highlights the importance of distinguishing preference statements from the weight these preferences carry in agents' utility.

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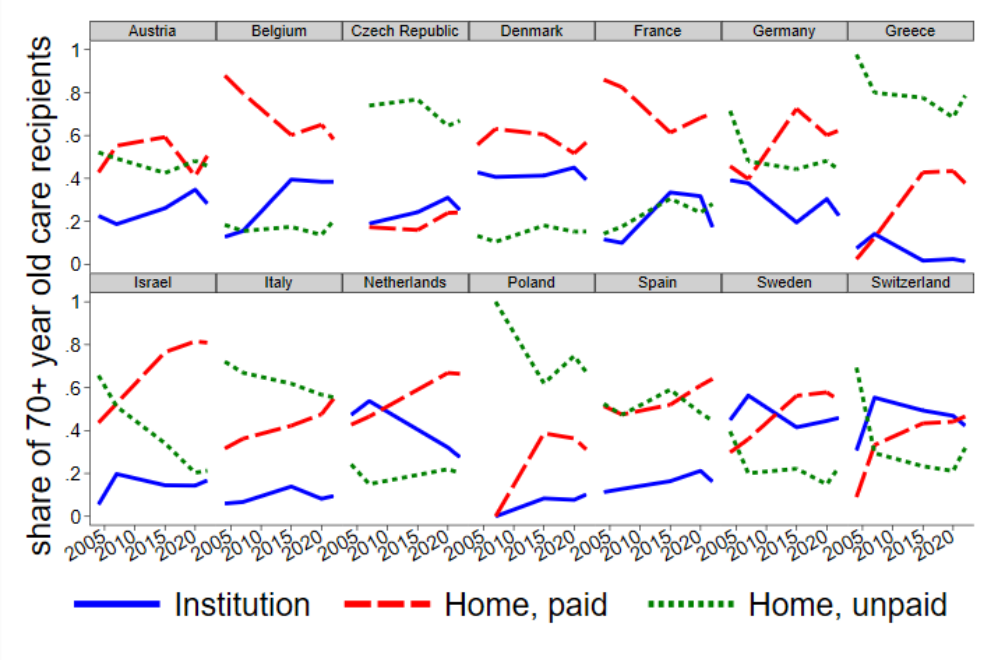
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APPENDIX - FOR ONLINE PUBLICATION ONLY

A Elderly care in Europe

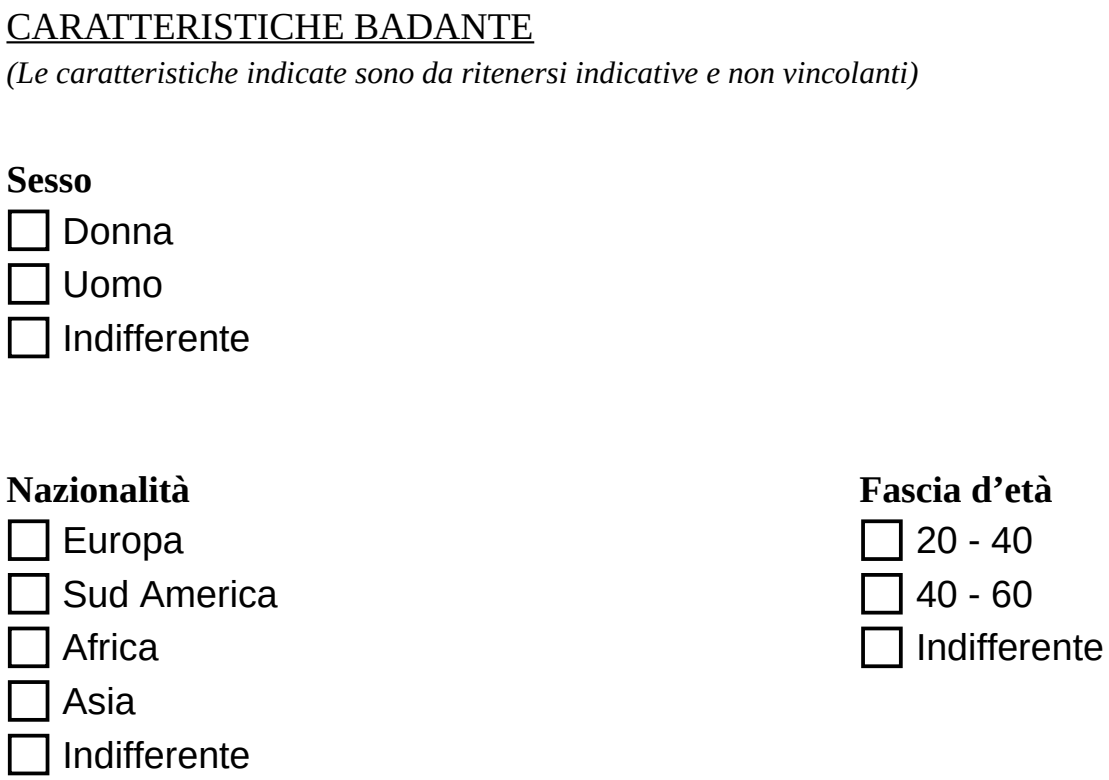
Figure A1: Share of 70+ year old care recipients by mode and country



Note: This figure shows the share of individuals aged 70 and above receiving institutional care, paid home care, or unpaid home care across selected European countries and Israel. Data are drawn from SHARE surveys, including only those waves where long-term care information was collected. Source: SHARE data 2004-2022.

B Questionnaire on client preferences

Figure A2: Questionnaire on client preferences over worker's characteristics



Note: This figure displays the last part of the company's questionnaire for clients, inquiring about preferences over a worker's personal characteristics. "CHARACTERISTICS OF CARER (*The characteristics indicated are to be considered indicative and not binding*) — **Sex** ☐ Woman ☐ Man ☐ Indifferent — **Nationality** ☐ Europe ☐ South America ☐ Africa ☐ Asia ☐ Indifferent — **Age range** ☐ 20-40 ☐ 40-60 ☐ Indifferent".

C Italian non-discrimination law

DECRETO LEGISLATIVO 9 luglio 2003 , n. 216 , Art. 3:

...Nel rispetto dei principi di proporzionalità e ragionevolezza e purché la finalità sia legittima, nell'ambito del rapporto di lavoro o dell'esercizio dell'attività di impresa, non costituiscono atti di discriminazione ai sensi dell'articolo 2 quelle differenze di trattamento dovute a caratteristiche connesse alla religione, alle convinzioni personali, all'handicap, all'età, alla nazionalità o all'orientamento sessuale di una persona, qualora, per la natura dell'attività lavorativa o per il contesto in cui essa viene espletata, si tratti di caratteristiche che costituiscono un requisito essenziale e determinante ai fini dello svolgimento dell'attività medesima...

(***In compliance with the principles of proportionality and reasonableness and provided that the purpose is legitimate****, in the context of the employment relationship or the exercise of the business activity, those* ***differences in treatment*** *due to characteristics connected to religion, personal beliefs, handicap, age, nationality or the sexual orientation of a person* ***do not constitute acts of discrimination*** *pursuant to article 2,* ***if, due to the nature of the work activity or the context in which it is carried out, these are characteristics that constitute an essential and decisive requirement*** *for the purpose of carrying out the activity itself.*)

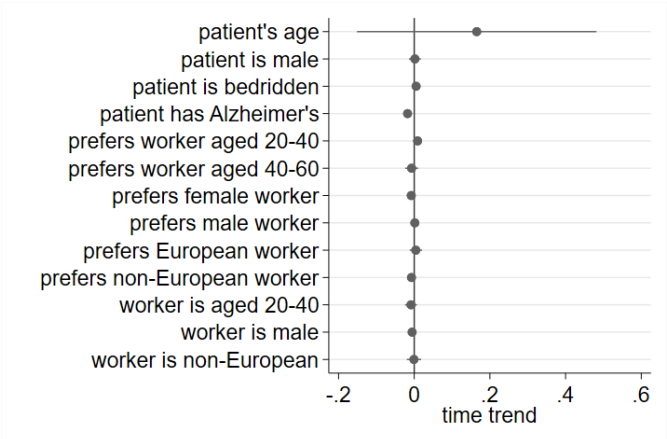
D Additional Descriptives

Table A1: Comparison with SHARE data

	(1) Agency data	(2) SHARE data	(3)
	Care worker	Care worker	Any type of care
Age	83.516	82.059	80.321
Female	0.696	0.664	0.693
Dementia	0.255	0.269	0.198
Difficulty getting in or out of bed	0.396	0.378	0.288
Observations	2,724	119	212

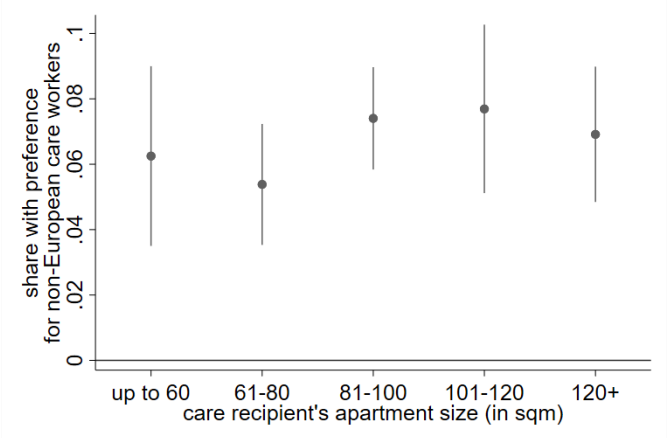
Notes: The table compares the internal firm administrative data to the nationally representative sample of Italian SHARE in the 2021/2022 wave. In column (2), the latter are restricted to respondents with a paid care worker at home. Column (3) shows characteristics of individuals receiving any type of care, including care by family members and institutional care. SHARE data do not distinguish Alzheimer's disease from other forms of dementia. In the agency data, I thus pool clients indicating Alzheimer's and or dementia for the care recipient. SHARE data do not indicate whether individuals are bedridden, but only whether they have difficulty "getting in or out of bed". In the agency data, I thus pool clients reporting that care recipients are either bedridden or insufficiently mobile.

Figure A3: No trends in characteristics or preferences



Note: This figure shows coefficients from separate regressions of client characteristics and preferences as well as of the corresponding characteristics of workers for all matches formed between January 2020 and June 2023 on a linear trend in years. Source: Firm administrative data.

Figure A4: Preferences for non-European care workers by clients' apartment size

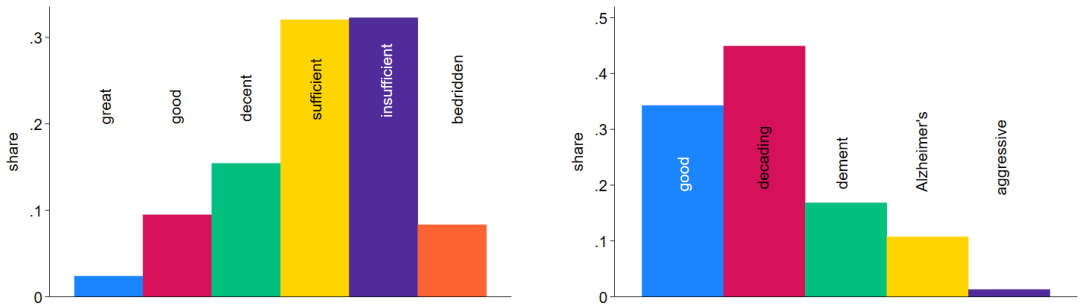


Note: The figure plots the share of clients indicating a preference for non-European workers by the care recipients' apartment size as a proxy for income. It does not support the notion that poorer clients are more inclined to request a non-European worker. Source: Firm administrative data.

Figure A5: Care recipients' cognitive and physical health

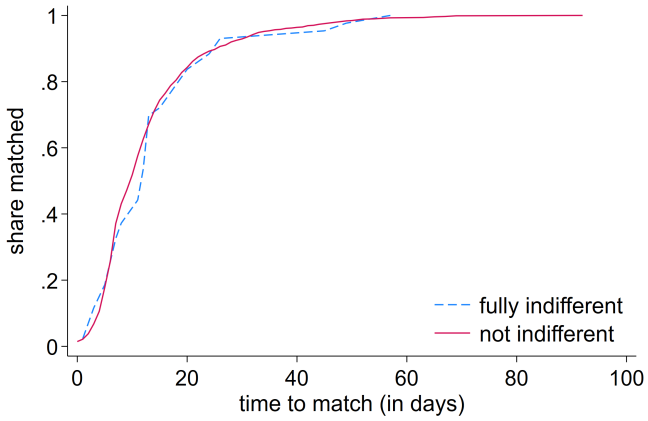
(a) Mobility

(b) Cognitive status



Note: This figure shows the distributions of care recipients' physical and cognitive health as elicited by the client questionnaire. Panel (a) displays the distribution of care recipients' mobility; Panel (b) shows the distribution of cognitive status (with potentially multliple choices). Source: Firm administrative data.

Figure A6: Client preferences and time until match formation

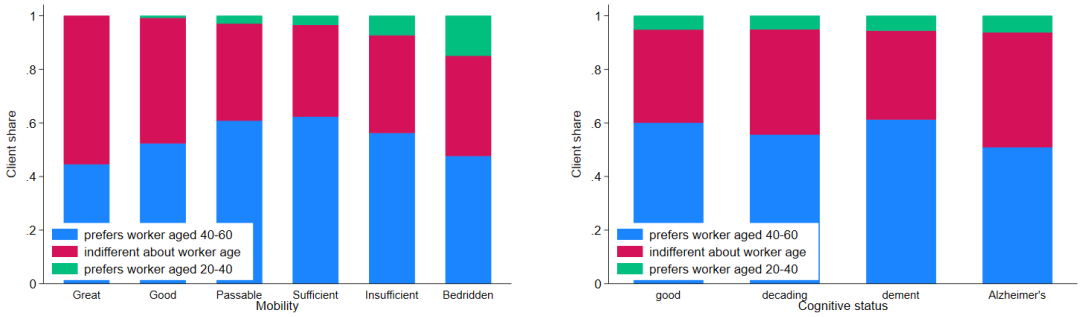


Note: This figure shows the cumulative distribution of time between a client's assignment to a caseworker searching for a care worker until the contract is signed. The figure distinguishes matches where the client is indifferent over workers' age, sex and origin (blue dashed line), and those where the client expressed a preference over at least one of these dimensions (red solid line). Source: Firm administrative data.

Figure A7: Care recipients' preferences over workers' age

(a) By mobility

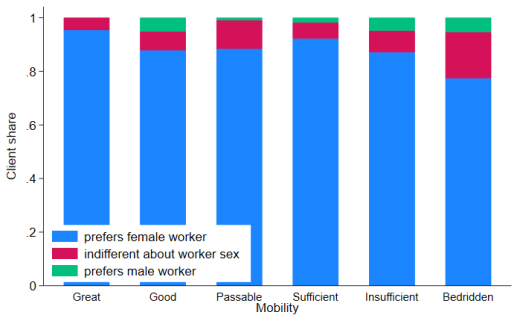
(b) By cognitive status



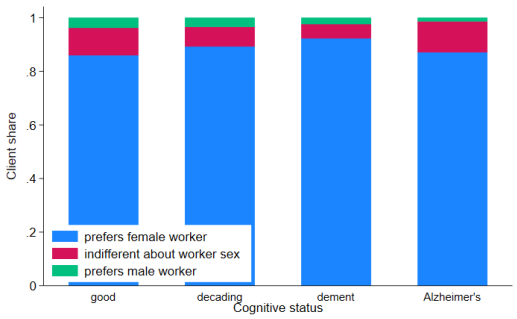
Note: This figure shows the distributions of clients' preferences over workers' age by care recipients' physical and cognitive health as elicited by the client questionnaire. Panel (a) displays age preferences by care recipients' mobility; Panel (b) shows age preferences by cognitive status. The preference distribution is not shown within "aggressive" care recipients due to the small number of observations. Source: Firm administrative data.

Figure A8: Care recipients' preferences over workers' sex

(a) By mobility



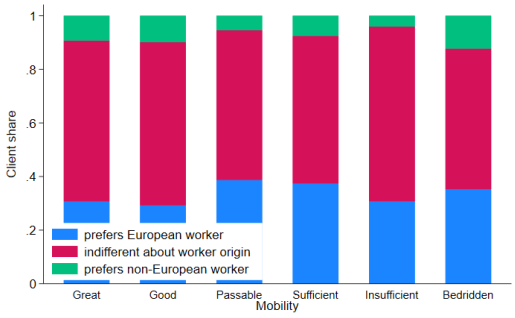
(b) By cognitive status



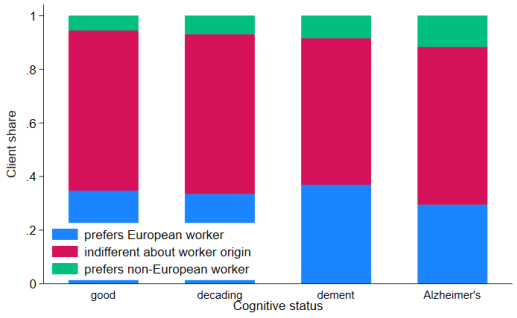
Note: This figure shows the distributions of clients' preferences over workers' sex by care recipients' physical and cognitive health as elicited by the client questionnaire. Panel (a) displays gender preferences by care recipients' mobility; Panel (b) shows gender preferences by cognitive status. The preference distribution is not shown within "aggressive" care recipients due to the small number of observations. Source: Firm administrative data.

Figure A9: Care recipients' preferences over workers' origin

(a) By mobility



(b) By cognitive status



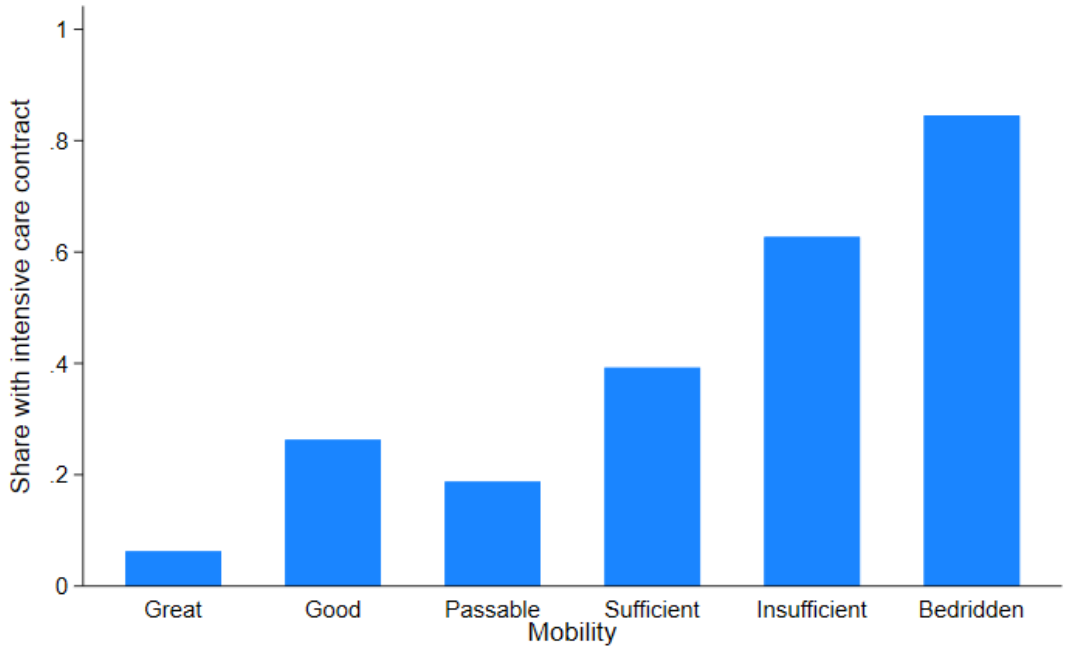
Note: This figure shows the distributions of clients' preferences over workers' origin by care recipients' physical and cognitive health as elicited by the client questionnaire. Panel (a) displays origin preferences by care recipients' mobility; Panel (b) shows origin preferences by cognitive status. The preference distribution is not shown within "aggressive" care recipients due to the small number of observations. Source: Firm administrative data.

Table A2: Client characteristics and intensive care contracts

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Intensive care contract Mean: 0.45				
Age	−0.005				−0.004
	(0.001)				(0.001)
Female		0.003			−0.003
		(0.021)			(0.020)
Alzheimer			−0.022		−0.018
			(0.031)		(0.030)
Bedridden				0.426	0.422
				(0.034)	(0.034)
Constant	0.851	0.448	0.454	0.419	0.786
	(0.090)	(0.029)	(0.010)	(0.010)	(0.095)
Observations	2,710	2,734	2,712	2,694	2,657

Note: The table shows correlations between client characteristics and contractual intensive care (Italian classification CS). Coefficients indicate the strong predictive power of being bedridden for an intensive care contract (see also Figure A10). Source: Firm administrative data.

Figure A10: Health condition and intensive care contracts



Note: The figure shows shares of contractual intensive care (Italian classification CS) by clients' mobility. Source: Firm administrative data.

E Potential misreporting of availabilities

This appendix investigates whether workers with less frequently demanded characteristics overstate their availability. Table A3 finds no evidence for a tendency by (less often demanded) non-European workers stating availability for working with Alzheimer's or bedridden patients to later quit. For Alzheimer's preferences the coefficients actually point in the opposite direction: when workers who report an availability to work with Alzheimer's patients and they end up being matched with an Alzheimer's patient, Europeans are more likely to quit, whereas non-Europeans are not. Similarly for young and male care workers. Tables A4 and A5 also show no evidence for misreporting by (less often demanded) younger or male care workers.

Table A3: Non-European workers' ex-ante availabilities and ex-post quits

	(1)	(2)	(3)	(4)
Dependent variable: Worker quits				
Alzheimer patient	0.119	0.106		
	(0.057)	(0.060)		
Alzheimer patient	-0.171	-0.144		
× non-European worker	(0.078)	(0.080)		
Bedridden patient			-0.018	-0.018
			(0.062)	(0.063)
Bedridden patient			0.035	0.063
× non-European worker			(0.092)	(0.093)
Year effects		X		X
Province effects		X		X
Characteristics		X		X
Sample: Worker available for				
	Alzheimer	Alzheimer	Bedridden	Bedridden
# Matches	1,057	1,055	1,085	1,082

Note: This table reports conditional correlations between match characteristics and the propensity for non-European workers to quit. Columns (1) and (2) include matches where workers declared availability for working with care recipients diagnosed with Alzheimer's. Columns (3) and (4) include matches where workers declared availability for working with bedridden care recipients. The dependent variable is an indicator for a worker quitting the job. Estimations in columns (2) and (4) control for year and province fixed effects, as well as for the worker's origin, age group and sex. Source: Firm administrative data.

Table A4: Young workers' ex-ante availabilities and ex-post quits

	(1)	(2)	(3)	(4)
Dependent variable: Worker quits				
Alzheimer patient	0.027	0.021		
	(0.044)	(0.046)		
Alzheimer patient	-0.021	0.028		
× young worker	(0.096)	(0.097)		
Bedridden patient			-0.011	0.002
			(0.051)	(0.052)
Bedridden patient			0.048	0.043
× young worker			(0.116)	(0.117)
Year effects		X		X
Province effects		X		X
Characteristics		X		X
Sample: Worker available for				
	Alzheimer	Alzheimer	Bedridden	Bedridden
# Matches	1,056	1,055	1,084	1,082

Note: This table reports conditional correlations between match characteristics and the propensity for workers aged 20-40 to quit. Columns (1) and (2) include matches where workers declared availability for working with care recipients diagnosed with Alzheimer's. Columns (3) and (4) include matches where workers declared availability for working with bedridden care recipients. The dependent variable is an indicator for a worker quitting the job. Estimations in columns (2) and (4) control for year and province fixed effects, as well as for the worker's origin, age group and sex. Source: Firm administrative data.

Table A5: Male workers' ex-ante availabilities and ex-post quits

	(1)	(2)	(3)	(4)
Dependent variable: Worker quits				
Alzheimer patient	0.003	0.011		
	(0.042)	(0.044)		
Alzheimer patient	0.124	0.122		
× male worker	(0.115)	(0.116)		
Bedridden patient			0.009	0.025
			(0.049)	(0.051)
Bedridden patient			-0.104	-0.113
× male worker			(0.139)	(0.140)
Year effects		X		X
Province effects		X		X
Characteristics		X		X
Sample: Worker available for				
	Alzheimer	Alzheimer	Bedridden	Bedridden
# Matches	1,057	1,055	1,085	1,082

Note: This table reports conditional correlations between match characteristics and the propensity for male workers to quit. Columns (1) and (2) include matches where workers declared availability for working with care recipients diagnosed with Alzheimer's. Columns (3) and (4) include matches where workers declared availability for working with bedridden care recipients. The dependent variable is an indicator for a worker quitting the job. Estimations in columns (2) and (4) control for year and province fixed effects, as well as for the worker's origin, age group and sex. Source: Firm administrative data.

F Do Workers Continue Informally?

Table A6 shows that 43% of matched workers are consecutively assigned to multiple contracts, suggesting that they do not continue informally with a client after a match is formally dissolved. The table furthermore shows that this is relatively more likely among non-European workers, that job durations are shorter, and that it actually is more common if a formal contract has ended. The data thus do not support a scenario in which clients terminate a contract soon after a match is formed in order to informally continue the employment relation.

Table A6: Repeated contracts by worker and match characteristics

	Multiple contracts	
	No	Yes
	57%	43%
Number of contracts	1	3.02
		(0.03)
Job duration (in days)	95.73	81.37
	(3.97)	(4.52)
Worker is Non-European	0.41	0.46
	(0.01)	(0.01)
Worker laid off	0.37	0.37
	(0.01)	(0.01)
Contract ended	0.17	0.21
	(0.01)	(0.01)
Observations	1,515	1,129

Note: The table shows the share among matched workers who had more than one contract. Each row of the table represents a separate regression of the row variable on indicators for whether a worker has repeated contracts.

G Employment duration and Match Quality

This appendix presents additional results on the relationship between match quality and duration. Figure A7 compares preferences by clients and workers to the characteristic in their match. Table A8 reports conditional correlations between employment duration and match quality, corresponding to the unconditional relation displayed in Figure 2d in the text.

Table A7: Match quality across different dimensions

Client preference over workers' age			
	20-40	indifferent	40-60
Share of workers aged $\leq$40	0.323	0.248	0.189
Client preference over workers' sex			
	female	indifferent	male
Share of male workers	0.025	0.387	0.667
Client preference over workers' origin			
	European	indifferent	non-European
Share of non-European workers	0.336	0.467	0.617
Worker preference over patients' sex			
	female	indifferent	male
Share of male clients	0.143	0.322	0.609
Worker preference over patients with Alzheimer's			
	available		not available
Share of clients with Alzheimer's	0.122		0.095
Worker preference over bedridden patients			
	available		not available
Share of bedridden clients	0.079		0.085

Note: The table compares match characteristics with agents' preferences over worker and care recipients' characteristics age, sex, origin and health conditions. Source: Firm administrative data.

Table A8: Match quality and employment duration

	(1)	(2)	(3)	(4)
Dependent variable: log employment duration (in days)				
Good match	0.229	0.247	0.208	0.158
	(0.071)	(0.075)	(0.075)	(0.067)
Province & year effects		X	X	X
Client & worker characteristics			X	X
Contract type				X
Observations	2,351	2,349	2,328	2,326
Mean (censored) duration: 125 days, Median duration: 41 days				

Note: The table reports conditional correlations between match quality, indicated by a match meeting clients' preferences over workers' age, sex and origin and workers' preferences over care recipients' sex, Alzheimer's and bedridden status, and employment duration, measured as the log number of days a job lasts. Standard errors reported in parentheses are clustered at the province level. Source: Firm administrative data.

H Likelihood Function

The final step of the estimation procedure maximizes a likelihood function that integrates the likelihood contributions from match formation, wage observation, and match separation (implying durations):

$$
\begin{aligned}
LL \;=\; & \sum_{m=1}^{N}\left(\frac{\tilde{\boldsymbol{x}}'_{i_m}\boldsymbol{A}\boldsymbol{y}_{j_m}+\boldsymbol{x}'_{i_m}\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_{j_m}-a(\tilde{\boldsymbol{x}}_{i_m})-b(\tilde{\boldsymbol{y}}_{j_m})}{\sigma_\varepsilon+\sigma_\eta}\right)\\
& -\sum_{m=1}^{N}\left(\frac{W_{i_m j_m}-\alpha-\frac{\sigma_\eta}{\sigma_\varepsilon+\sigma_\eta}\left(\tilde{\boldsymbol{x}}'_{i_m}\boldsymbol{A}\boldsymbol{y}_{j_m}-a(\tilde{\boldsymbol{x}}_{i_m})\right)-\frac{\sigma_\varepsilon}{\sigma_\varepsilon+\sigma_\eta}\left(b(\tilde{\boldsymbol{y}}_{j_m})-\boldsymbol{x}'_{i_m}\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_{j_m}\right)}{2\sigma_\omega^2}\right)\\
& -\frac{N}{2}\log\sigma_\omega^2\\
& +\sum_{m=1}^{N}\Big(separated_m\left(-duration_m\Big/(\delta\bar{V}_{i_m,j_m})-\log(\delta\bar{V}_{i_m,j_m})\right)\\
& +(1-separated_m)\left(-duration_m\Big/(\delta\bar{V}_{i_m,j_m})\right)\Big),
\end{aligned}
\tag{11}
$$

where the term

$$
\bar{V}_{i_m,j_m}=\tilde{\boldsymbol{x}}'_{i_m}\boldsymbol{A}\boldsymbol{y}_{j_m}+\boldsymbol{x}'_{i_m}\boldsymbol{\Gamma}\tilde{\boldsymbol{y}}_{j_m}-(\sigma_\varepsilon+\sigma_\eta)\log\big(\pi(i_m,j_m)\big) \tag{12}
$$

captures the expected match surplus for each observed match m. The first row in (11) corresponds to match probabilities (7); the second and third rows capture the likelihood of observing wages as determined by (10); whereas the last two rows reflect censored and uncensored match durations.

I Additional Parameter and Surplus Estimates

Table A9 lists the remaining model parameters. Specifically, I estimate a baseline surplus level V_0 of 14.60 euros/hour. This applies to matches between female clients without Alzheimer's who are not bedridden and who are indifferent about worker characteristics and female European workers aged 40-60 who are available for work with patients of either sex and who do not state an availability for working with Alzheimer's or bedridden patients.

Table A9: Other estimated parameters

Parameter		Estimate	Std.err.
Baseline surplus level	V_0	14.596	(0.914)
Hazard factor	δ	9.603	(0.841)
Idiosyncratic client tastes	σ_ε	0.231	(0.029)
Idiosyncratic worker tastes	σ_η	0.006	(0.059)
Wage intercept	α	2.694	(0.165)
Wage standard deviation	σ_ω	1.203	(0.003)

Note: This table presents additional estimated parameters from the matching model. The baseline surplus level (V_0) represents the baseline match surplus, while the hazard factor (δ) scales inverse match surpluses to the hazard rates. The parameters σ_ε and σ_η denote the spread of unobserved client and worker preferences, respectively, influencing match probabilities. The wage intercept (α) reflects the discrepancy between observed wages and true underlying transfers, while σ_ω captures the variation in observed wage data relative to true transfers. Source: Firm administrative data.

To determine the distribution of this surplus between clients and workers, I assume that surplus shares net of wages are inversely proportional to matches being dissolved by either side of the match. Specifically, I follow these steps:

1. Regress indicators for a client dissolving the match on client and worker characteristics and preferences.

2. Predict probability $\hat{p}_0^c$ of the client dissolving the match if they and the worker were baseline types (indicated by 0).

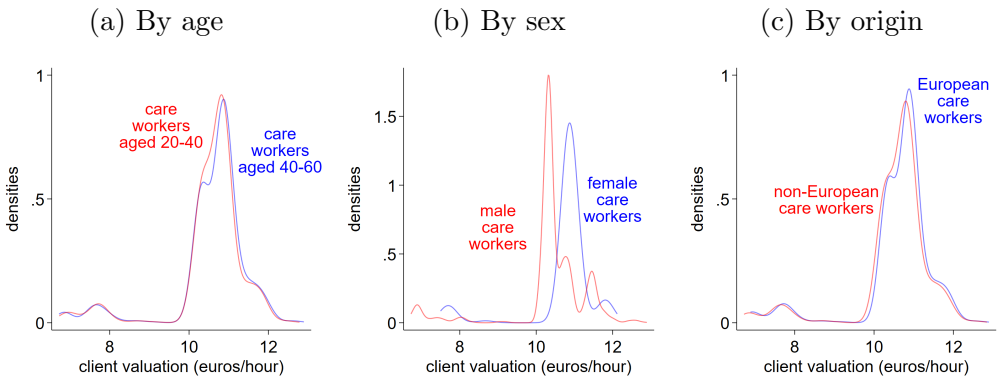
3. Repeat these predictions also for workers' probability $\hat{p}_0^w$ of dissolving the match and for wages $\hat{w}_0$.

4. Assume the worker's surplus share $\frac{\hat{w}_0+u_0^w}{V_0}$ of a match between baseline types equals the share $\frac{\hat{p}_0^c}{\hat{p}_0^c+\hat{p}_0^w}$ of dissolved matches that were terminated by the client, where u_0^w denotes the unknown share of the total baseline surplus V_0 that goes to the worker.

5. Compute a client's share of the baseline surplus as $V_0 - u_0^w = V_0 - \frac{\hat{p}_0^c V_0}{\hat{p}_0^c+\hat{p}_0^w} + \hat{w}_0$.

Figure A11 displays the resulting densities of client valuations for different types of care workers. The figure reveals client surpluses ranging between 10 and 12 euros per hour for most clients. Panel (a) shows that the higher baseline payoff generated by younger care workers to clients who are indifferent about a worker's age is dominated by the preference for older workers held by a majority of clients. In Panel (b), the higher baseline payoff from male workers erodes the strong preference bias of clients towards female workers, with a remaining median difference in client payoffs of 53 cents per hour in favor of female workers. European care workers generate about the same baseline payoff as non-Europeans, but are preferred by about a third of clients. Across all origin preferences, the mean client surplus from European workers exceeds that from non-European workers by only 7 cents per hour (Panel (c)). Distributions in Figure A11 are hypothetical in that valuations are predicted for each client irrespective of the type of worker they actually employ.

Figure A11: Unscaled distributions of client valuations for different types of workers.



Note: The figure shows distributions of client valuations for different types of care workers. Distributions are hypothetical in that valuations are predicted for each client irrespective of the type of worker they employ. Panel (a) distinguishes care workers by age; Panel (b) by sex; Panel (c) by origin. Source: Estimates of client valuations from the model using company administrative data.

J Restricted model without preferences

This appendix presents estimates of client and worker payoff matrices in a restricted model that does not account for stated preferences, equivalent to setting the upper parts of the payoff matrices displayed in Tables 3 and 4 in the text to zero.

Table A10: Client valuation estimates if not accounting for stated preferences

	Young worker	Male worker	Non-European worker	Baseline effect
Patient Characteristics				
Patient is male	-0.217	0.607	-0.019	0.185
	(0.000)	(0.017)	(0.005)	(0.005)
Patient is bedridden	0.097	-0.020	0.003	-3.038
	(0.004)	(0.006)	(0.005)	(0.010)
Patient has Alzheimer	-0.018	0.191	-0.014	0.948
	(0.005)	(0.005)	(0.006)	(0.023)
Baseline effect	0.002	-0.049	-0.234	
	(0.007)	(0.006)	(0.005)	

Note: This table shows client valuations for different match characteristics estimated from a model constraining $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ to exclude stated preferences. Asymptotic standard errors are reported in parentheses.

Table A11: Worker valuation estimates if not accounting for stated preferences

	Male patient	Bedridden patient	Alzheimer patient	Baseline effect
Worker Characteristics				
Worker is young	0.158	-0.080	0.009	-0.101
	(0.007)	(0.007)	(0.006)	(0.007)
Worker is male	0.083	-0.008	-0.067	0.342
	(0.006)	(0.005)	(0.006)	(0.011)
Worker non-European	0.002	-0.022	0.087	-0.187
	(0.006)	(0.006)	(0.006)	(0.009)
Baseline effect	-0.243	-0.963	-0.016	
	(0.005)	(0.006)	(0.005)	

Note: This table shows worker valuations for different match characteristics estimated from a model constraining $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ to exclude stated preferences. Asymptotic standard errors are reported in parentheses.

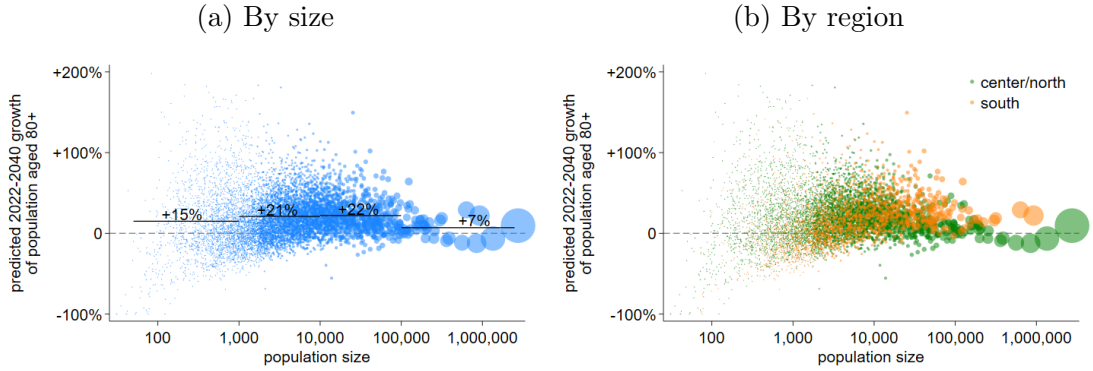
Table A12: Other parameters in a restricted model not accounting for preferences

Parameter		Estimate	Std.err.
Baseline surplus level	V_0	14.708	(0.497)
Hazard factor	δ	9.512	(0.355)
Idiosyncratic client tastes	σ_ε	0.232	(0.024)
Idiosyncratic worker tastes	σ_η	0.011	(0.025)
Wage intercept	α	2.636	(0.079)
Wage standard deviation	σ_ω	1.202	(0.006)

Note: This table shows additional estimated parameters from a model constraining $\boldsymbol{A}$ and $\boldsymbol{\Gamma}$ to exclude stated preferences. The baseline surplus level (V_0) represents the baseline match surplus, while the hazard factor (δ) scales inverse match surpluses to the hazard rates. The parameters σ_ε and σ_η denote the spread of unobserved client and worker preferences, respectively, influencing match probabilities. The wage intercept (α) reflects the discrepancy between observed wages and true underlying transfers, while σ_ω captures the variation in observed wage data relative to true transfers. Source: Firm administrative data.

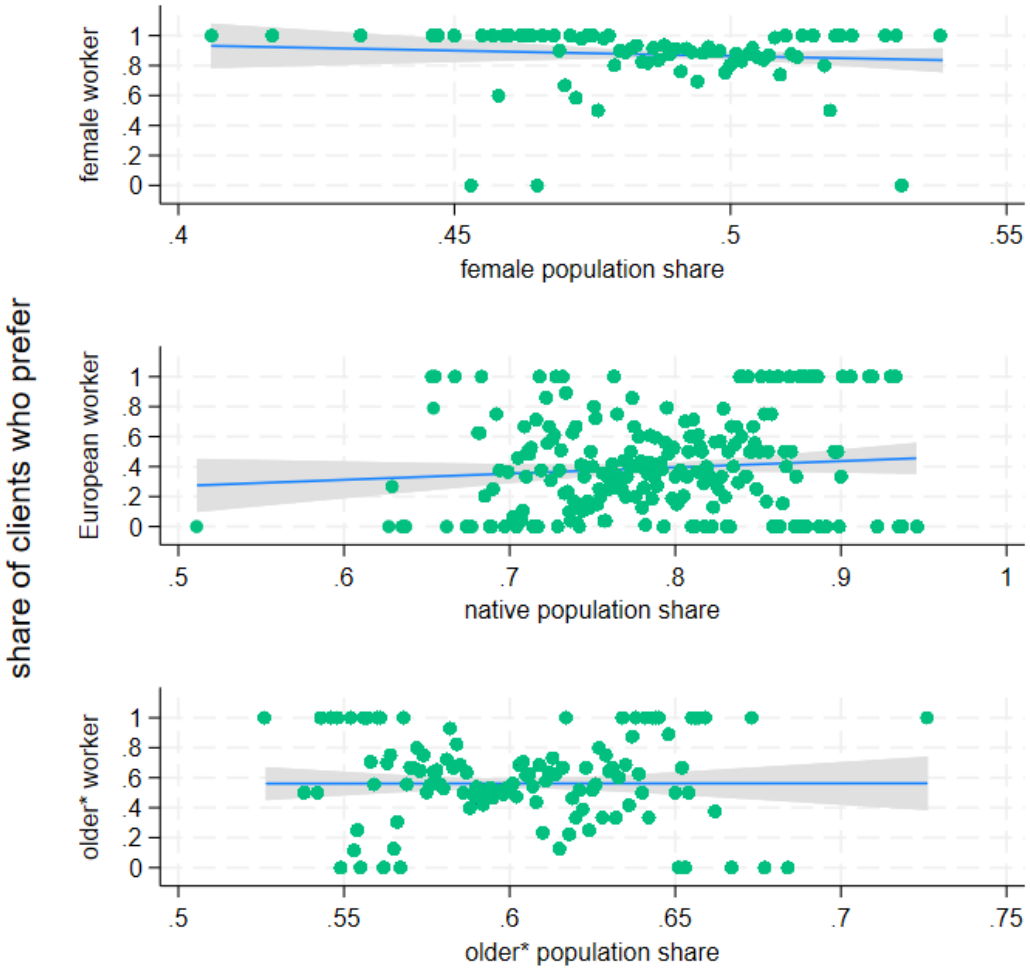
K Additional figures on client preferences and demographic projections

Figure A12: Projected percentage growth in the 80+ population.



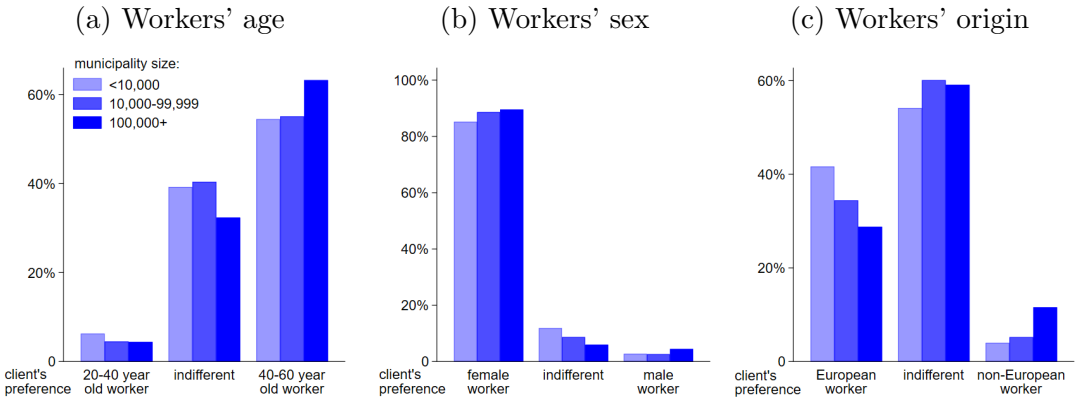
Note: Panel (a) shows the projected growth rate in the adult population aged 80 and older between 2022 and 2040 across municipalities of different sizes. Panel (b) further differentiates these projections by region, highlighting differences between southern and central/northern Italian municipalities. Dot areas are proportional to total population. Source: Own computation based on ISTAT municipal population register data 2015-2022.

Figure A13: No statistical relation between preferences and local populations



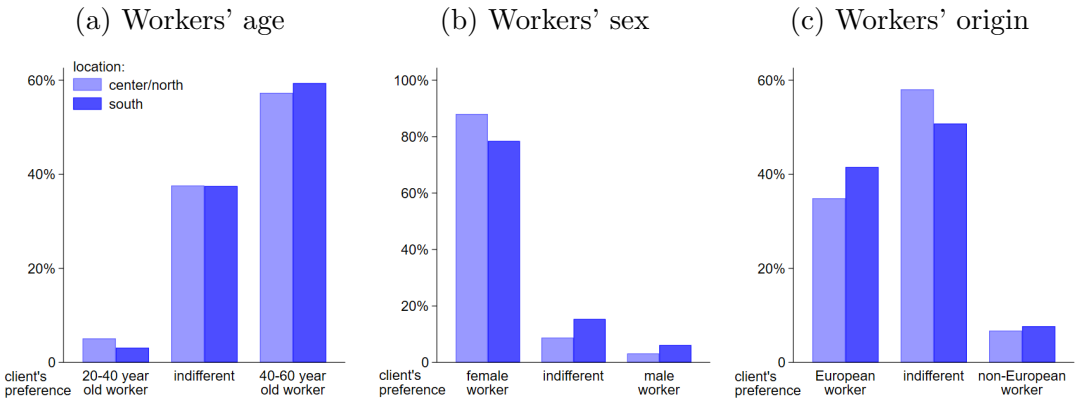
Note: The figure shows correlations between population characteristics within municipalities from population registers and client preferences for caregiver sex (top), origin (middle) and age (bottom) from the agency data. ISTAT population registers only distinguish native and foreign born residents, not Europeans versus non-Europeans as in the agency data. Source: ISTAT and firm administrative data.

Figure A14: Client preferences by municipality size



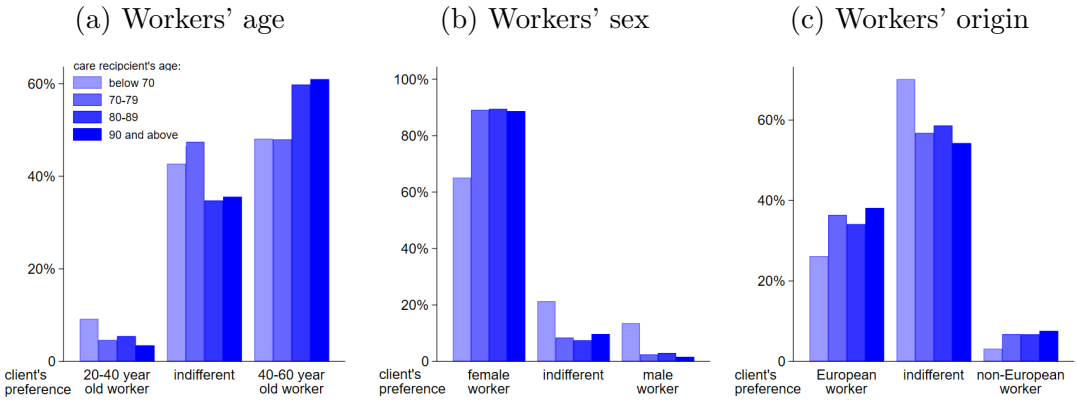
Note: The figure shows client preferences for (a) caregiver age, (b) sex, and (c) origin by municipality size. Source: Firm administrative data.

Figure A15: Client preferences by region



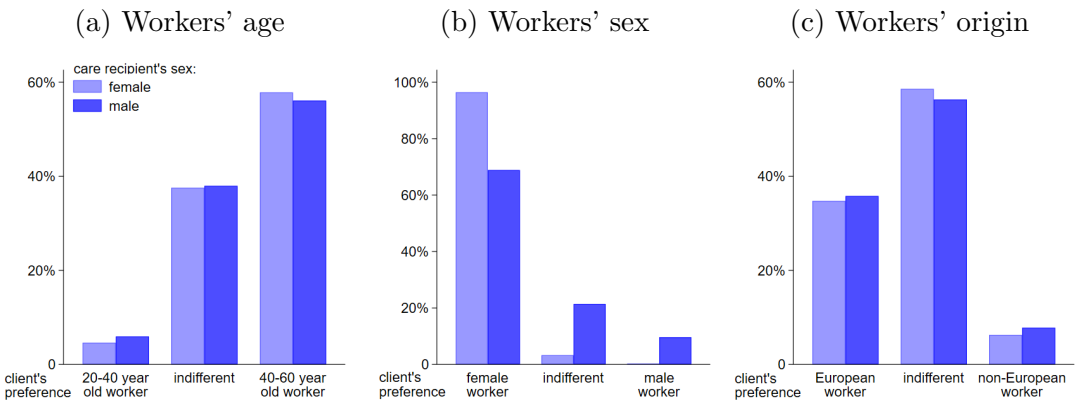
Note: The figure shows client preferences for (a) caregiver age, (b) sex, and (c) origin by region. Source: Firm administrative data.

Figure A16: Client preferences by client age



Note: The figure shows client preferences for (a) caregiver age, (b) sex, and (c) origin by age of the client. Source: Firm administrative data.

Figure A17: Client preferences by client sex



Note: The figure shows client preferences for (a) caregiver age, (b) sex, and (c) origin by sex of the client. Source: Firm administrative data.