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Sorting in Marriage Markets: The Role of Non-Wage Amenities*

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Abstract

Partners often match on similar characteristics, such as demographics and wages, contributing to inequality between households. We study whether non-wage job amenities—an important part of compensation in the labor market that may also affect household production—play a role in marriage sorting. Using linked survey and administrative data from Germany, we infer individuals' expected future job attributes from their jobs at the time of matching and estimate a frictionless transferable-utility model. We find positive assortative matching on lifetime earnings, part-time work potential, and schedule regularity, suggesting complementarities within households. In contrast, we find no evidence of sorting on work meaning. Counterfactual simulations show that while assortative matching increases inequality overall, sorting on non-wage amenities slightly reduces it, lowering the Gini coefficient of total compensation by 3.3 percent.

Keywords: marriage market, assortative matching, non-wage amenities, household inequality

JEL Classification: D1, D31, J12

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1 Introduction

Individuals tend to choose partners who are similar to them, for example, in terms of age, earnings or education (Dupuy and Galichon, 2014; Chiappori, Ciscato, and Guerriero, 2024), a phenomenon called homogamy or positive assortative matching. Positive assortative matching on education or earnings increases between-household inequality (Greenwood et al., 2014; Eika, Mogstad, and Zafar, 2019; Almar et al., 2025). While recent literature shows that in labor markets, not only earnings but also non-monetary aspects of work, or amenities, contribute to sorting and inequality (Maestas et al., 2023; De Schouwer and Kesternich, 2025), one question that has received little attention is whether those non-wage amenities also matter for sorting in the marriage market. The recent labor literature argues that not only wages, but total compensation, the sum of wages and valuations for amenities, matter for labor market inequality. Likewise, marriage matching on amenities might have important implications for between-household inequality.

Consequently, in this paper, we investigate the importance of job amenities for matching patterns, where we proxy expected future job characteristics using the spouses' jobs at the time of matching. In a second step, we investigate how sorting on amenities affects between-household inequality.

We employ a frictionless transferable utility matching model (Choo and Siow, 2006; Dupuy and Galichon, 2014), in which marital surplus, i.e., the gain from matching, governs the static equilibrium matching patterns. We use a quadratic parameterization of marital surplus, building upon an 'affinity matrix' which measures mutual attractiveness between any considered characteristics of partners. Becker (1973) connects marital surplus to household production. We think of amenities as potential inputs in the production of household goods, such as child welfare. The way both partners' amenities interact in the production function determines how well partners with specific job characteristics can produce household goods.

Estimating the model requires information on formed couples, occupations at the time of matching, and associated expected amenities. We extract this information from three German data sources. We take information on spouses from the German Socio-Economic Panel (GSOEP) and derive gender-occupation-specific measures of amenities from the Sample of Integrated Labor Market Biographies (SIAB) and the BIBB/BAuA Employment Survey. Using linked GSOEP-SIAB data, we identify each individual's occupation at the time of matching and assign expected amenities based on gender-occupation-specific averages. We assume that individuals form expectations about a partner's future job characteristics based on their current occupation, as proxied by these averages. This approach captures ex ante job characteristics at the time of matching, rather than realized outcomes. We see this as a strength as, for instance, it allows us to account for the part-time potential of a job even if the spouse is not yet working part-time at the time of matching.

Specifically, the non-wage amenities we consider are (i) schedule regularity, (ii) the potential to work part-time, and (iii) work meaning. The former two are important dimensions of labor market flexibility, which is central to a literature in labor economics that investigates how gender differences in preferences for these amenities translate into gender wage gaps (Mas and Pallais, 2017; Wiswall and Zafar, 2018) and how labor market flexibility influences within-couple time allocation (Goldin, 2014; Calvo, Lindenlaub, and Reynoso, 2024; von Gaudecker et al., 2026). While we expect schedule regularity and part-time work to be relevant inputs for producing household commodities like child welfare and household services (Bang, 2021; Kesternich, Vermeulen, and Wintzéus, 2024), it remains an open question whether the characteristics of both partners function as complements or substitutes to each other. On the one hand, under traditional household specialization or with "greedy jobs" (Goldin, 2014), it might be sufficient if one spouse has a flexible job. On the other hand, for a mother with a flexible job, it might be especially relevant that the father also has a flexible job and can take over a part of childcare responsibilities, while a mother with an inflexible job might plan to reduce labor supply and/or drop out of the labor market once they have children. Behavioral economists care about how firms can use work meaning or mission to attract motivated workers, increase worker productivity, and lower reservation wages (Kosfeld, Neckermann, and Yang, 2017; Cassar and Meier, 2018; Ashraf et al., 2020; Kesternich, Schumacher, et al., 2021). While work meaning is important for labor market sorting (De Schouwer, Deneus, and Forti, 2025), it is less clear whether there is a relation to marital surplus.

In addition to these amenities, our matching model includes the demographic variables age at matching and years of schooling, as well as expected full-time lifetime earnings. The estimated affinity matrix, therefore, identifies complementarities in marital surplus associated with spouses' amenities conditional on complementarities in demographic characteristics. This is important as non-wage amenities are correlated with demographic variables such as education.

A challenge for our analysis of matching on job characteristics is that spouses often meet at work, which mechanically leads to assortative matching. In our analyses, we proxy this by including occupation as a categorical attribute in our model (Ciscato, Galichon, and Goussé, 2020), which ensures that our estimates are not biased by spouses working in the same occupation.

We find strong evidence for positive assortative matching on part-time potential, lifetime earnings, and schedule regularity, in decreasing order of the size of mutual attractiveness. The sum of marital gains is maximized if, for instance, high schedule regularity men match with high schedule regularity women and vice versa. This indicates complementarities in marital surplus along these dimensions. The coefficient for work meaning is positive, but small compared to that of the other amenities and statistically not significant. These findings are consistent with an interpretation in which the estimated complementarities in marital surplus arise from complementarities in household production, which are plausibly weaker for work meaning.

Additionally, we find that women who have high (low) earnings tend to match with men in jobs with low (high) schedule regularity, suggesting substitutability in household production between those spousal characteristics. Reassuringly, the coefficients for age and education indicate positive assortative matching and confirm the results of previous literature.

Beyond identifying who marries whom, we assess how marital sorting on non-wage amenities contributes to between-household inequality. We use our model to run counterfactual simulations of matching patterns. To measure associated inequality, we compute the Gini coefficient of couple-level earnings and couple-level total compensation, where the latter also accounts for the valuation of non-wage amenities. We calculate total compensation in a 'back-of-the-envelope' manner using gender-specific willingness-to-pay estimates from discrete choice experiments (Wiswall and Zafar, 2018; De Schouwer and Kesternich, 2025).

Comparing the Gini coefficient of earnings and total compensation, estimated matching patterns suggest that inequality increases by 8.6% when we take the valuation of non-wage amenities into account. This is in line with previous literature, showing that high-earning individuals tend to also have higher-valued amenities (Maestas et al., 2023).

Making use of the structural model, we then analyze counterfactual matching preferences and the resulting matching patterns and inequality. We first find that in line with previous literature, marriage matching contributes to between-household inequality: If spouses chose each other randomly, the Gini coefficient for total compensation would be 12.4% lower. Second, we examine how sorting specifically on non-wage amenities contributes to between-household inequality and find a small mitigating effect: if individuals no longer considered the potential to work part-time, schedule regularity, and work meaning when selecting a partner, inequality would increase by 3.3 percent (equivalent to 0.5 Gini points). In this counterfactual, sorting on earnings becomes relatively more important as sorting on non-wage amenities is removed. In addition, off-diagonal elements of the affinity matrix contribute to this pattern – for example, low-earning women tend to match with men who have high schedule regularity, which is itself positively associated with earnings.

Our paper contributes to the literature investigating who marries whom, which has primarily looked at demographic variables—such as age, education, and race—and earnings (e.g., Ciscato, Galichon, and Goussé, 2020; Ciscato and Weber, 2020; Chiappori, Fiorio, et al., 2022). A small set of papers goes beyond these characteristics, in particular personality traits (Dupuy and Galichon, 2014), risk attitudes (Dohmen et al., 2012; Ciscato, Do, and Nguyen, 2024), and health-related characteristics, such as Body Mass Index (Chiappori, Oreffice, and Quintana-Domeque, 2012) or smoking behaviors (Clark and Etilé, 2006). Calvo, Lindenlaub, and Reynoso (2024) estimate a joint equilibrium model of marriage market sorting on education and labor market sorting. Using German data, they find strong complementarities in spouses' home hours, reinforcing sorting in labor and marriage markets. Building on the insight that marriage and labor markets are related, we examine how occupation-specific job characteristics shape marital sorting.

A small literature looks at the relevance of job characteristics for marriage market decisions. Fisman et al. (2006) examine preferences about potential partners in a speed dating setting and find that women generally value job ambition while men only do so as long as the ambition of the woman does not exceed their own. Bursztyn, Fujiwara, and Pallais (2017) show that female MBA students moderate their career ambition (e.g., working long hours or traveling for work) to appeal to male peers. These studies document a tradeoff between looking favorable in the marriage market and career goals, while in the same vein, Folke and Rickne (2020) show that women's promotions are associated with a higher probability of divorce. While this literature highlights the relevance of job attributes for partner selection, we contribute by estimating an equilibrium matching model that allows us to analyze complementarities in marital surplus and enables counterfactual simulations.

Finally, we contribute to the literature on the valuations of amenities. Previous research has focused on their valuation in the labor market and their impact on wage inequality (e.g., Maestas et al., 2023). In contrast, our paper examines the valuation of amenities in the marriage market and between-household inequality. We confirm the finding that inequality is larger when the researcher includes the valuation of amenities. However, the behavioral effect of amenities on inequality differs: If individuals did not take amenities into account on the marriage market, between-household inequality would be slightly larger.

The paper is structured as follows: Section 2 sketches the transferable utility matching model, Section 3 describes the data, and Section 4 presents results. Section 5 includes the counterfactual simulations before Section 6 concludes.

2 Theoretical framework

In this section, we sketch a multidimensional transferable utility matching model (see Chiappori, 2017, for a detailed discussion of transferable utility models) which we later estimate. It allows us to recover a structural object – the joint surplus function – that directly entails complementarities between partner continuous characteristics (Dupuy and Galichon, 2014).

Men and women meet on a two-sided marriage market and form different-sex couples (Shapley and Shubik, 1971; Becker, 1973, 1974).[1] Each potential match between a man and a woman generates a joint surplus. One of the key assumptions of the model is that this surplus can be freely redistributed between spouses through transfers and that individuals can commit to the distribution before matching. Becker (1973) connects marital surplus to household production. If two individuals decide to form a couple, they can combine time and market goods to produce household com-

[1] We focus on different-sex couples for simplicity and because we only observe a few same-sex couples in our data. For a comparison of homogamy in same-sex and different-sex couples, see Ciscato, Galichon, and Goussé (2020).

modities. In the household production function, the nature of inputs - whether complementary or substitutable - explains whether positive or negative assortative matching occurs. For instance, if the time spent on household tasks by spouses is complementary, they tend to allocate a similar amount of time to household chores and, as a consequence, to time spent working on the labor market. This would result in positive assortative matching in working hours and wages. Conversely, negative assortative matching, or household specialization, arises if the partners' time inputs are substitutable in home production. Similarly, amenities can function as direct inputs in the household production function or shift the productivity of other inputs.

Each individual makes offers to potential partners, where an offer consists of how much surplus they are willing to transfer to secure that match. Since everyone simultaneously competes for their preferred partners, these transfers are determined by market forces. The equilibrium matching is stable as everyone is already matched to their best available option given the prevailing "prices" (transfers) in the market. A key result is that the individual level equilibrium matching coincides with the outcome that maximizes total (aggregate) social surplus (Koopmans and Beckmann, 1957; Shapley and Shubik, 1971; Becker, 1973). Intuitively, because transfers are frictionless, any stable allocation must exhaust all mutually beneficial reallocations, which leads the decentralized equilibrium to coincide with the surplus-maximizing assignment.

To estimate equilibrium matching patterns (who marries whom) and individual payoffs (surplus division), assumptions on the form of marital surplus generated by the match are necessary.

Populations. In our model, men are characterized by a vector of characteristics $x \in \mathbb{R}^x$ and women are characterized by a vector of characteristics $y \in \mathbb{R}^y$. A *matching* is the probability distribution $\pi(x, y)$ that a couple of types (x, y) appears.

Utility. Following the separable extreme value approach by Choo and Siow (2006), we assume that partners match on observed and unobserved characteristics. The unobserved heterogeneity term $\epsilon_{ij}(x, y)$ is additive separable in individual specific terms ruling out interactions of unobserved characteristics of potential spouses. That is, for any match of a man i of type $x_i = x$ and a woman j of type $y_j = y$, the surplus generated can be written as

$$\Phi(x, y) + \epsilon_{ij}(x, y) = \Phi(x, y) + \gamma_i(x) + \eta_j(y) \tag{1}$$

where $\gamma_i(x)$ and $\eta_j(y)$ are random sympathy shocks (following a Poisson point process) drawn by men and women, respectively. The deterministic surplus is denoted $\Phi(x, y)$.

Marital surplus. We make an assumption on the form of marital surplus $\Phi(x, y)$ and follow Ciscato, Galichon, and Goussé (2020) by using an affinity matrix A for continuous characteristics while also allowing for categorical variables:

$$\Phi_A(x, y) = (x^s)' A y^s + \lambda_o \mathbf{1}\left[x^o = y^o\right] , \tag{2}$$

where x^s and y^s are continuous characteristics and x^o and y^o are categorical variables. The coefficients A_{ij} of the affinity matrix measure mutual attractiveness between attribute x_i^s of the man and attribute y_j^s of the woman as $\frac{\partial^2 \Phi(x^s, y^s)}{\partial x_i^s \partial y_j^s}$. Specifically, it represents the change in the marginal effect of the man's attribute on joint utility if the attribute of the woman increases. The λ_o coefficient captures the degree of sorting on categorical variables.

Depending on the sign of the coefficients, the affinity matrix reveals complementarity ($A_{ij} > 0$) or substitutability ($A_{ij} < 0$) of the joint utility function. A positive coefficient indicates that high x_i^s men profit especially from having high y_j^s partners instead of low y_j^s partners. This would indicate that the sum of joint utilities in the marriage market is maximized if high x_i^s men match with high y_j^s women and vice versa. This should not be confused with absolute attractiveness. The affinity matrix does not indicate whether joint utility tends to be higher for high or low y_j^s women, just how the joint utility difference between high and low y_j^s women depends on men's characteristics.

Importantly, these coefficients measure mutual attractiveness conditional on all other considered variables. This is relevant if matching variables are correlated on the individual level.

Estimation. We estimate the affinity matrix by matching model predictions to observed data following Ciscato, Galichon, and Goussé (2020). The estimation relies on the fact that the decentralized equilibrium maximizes total social surplus (Shapley and Shubik, 1971). This optimization ensures that model-predicted co-moments match their empirical counterparts:

$$\mathbb{E}_\pi[X_i Y_j] = \mathbb{E}_{\hat{\pi}}[X_i Y_j] \tag{3}$$

for all characteristic pairs (i, j) where $\hat{\pi}$ denotes the empirical matching distribution. λ_o is identified by the moment-matching condition: $\Pr_{\pi}(x^o = y^o) = \Pr_{\hat{\pi}}(x^o = y^o)$. The procedure iteratively adjusts the affinity matrix parameters until the model replicates observed matching patterns (Ciscato and Weber, 2020).

Identification relies on the equilibrium relationship between marital surplus and the observed matching probabilities $\pi(x, y)$. The assumption of separable random sympathy shocks $\gamma_i(x)$ and $\eta_j(y)$ following a Poisson point process ensures point identification of marital surplus (Gualdani and Sinha, 2023).

3 Data and descriptive statistics

3.1 Data sources

Our analysis requires precise data on the formation of couples, occupations at relationship formation, and detailed data on wage and non-wage attributes of occupations. The German data environment is ideally suited for this endeavor, and we build upon three different sources of data.

GSOEP. The German Socio-Economic Panel (GSOEP) is a household panel of roughly 25,000 households drawn from the German population (Goebel et al., 2019). It collects individual and household-level data on demographic and socioeconomic characteristics. From the panel data, we identify the relevant couples, determine their respective cohabitation dates, and gather key characteristics such as age, education, and occupation. We append the biography data with detailed information on current and past relationships for couples who are observed after cohabitation only.

SIAB. The administrative employment history contains rich information on (un)employment spells, type of employment, earnings, occupations, and demographics at the individual level. We make use of the Sample of Integrated Labor Market Biographies (SIAB) in two ways. First, we identify the occupation at the time of couple formation by exploiting the link between the GSOEP and the SIAB (Antoni et al., 2025).[2] Second, we use the full SIAB to generate key characteristics of occupations, namely earnings and part-time potential.

[2] Since 2019, GSOEP respondents have been asked to give consent to link their (previous) information, and about 75% of them do so.

BIBB/BAuA Employment Survey. For other amenities, we rely on the representative BIBB/BAuA Employment Survey conducted in 2018 by the Federal Institute of Vocational Education and Training (Bundesinstitut für Berufsbildung—BIBB) and the German Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin—BAuA) (Hall, Siefer, and Tiemann, 2012). It contains data on working conditions, job satisfaction, meaning, and demographics. We make use of information on meaning—the feeling of doing useful work—and schedule regularity.[3]

3.2 Sample construction

We start by using the GSOEP, where we consider different-sex couples and define cohabitation as the moment of couple formation.[4] We focus on couples formed between 2010 and 2021 in which the woman is aged between 18 and 40 years old to capture individuals in their prime working and fertility age.

We restrict our sample to couples for whom we can observe (or infer) the age, education, and occupation of both partners at the time of cohabitation. To determine the occupation at couple formation of both spouses, we primarily make use of the SIAB. If one of the partners is unemployed or self-employed at the time of cohabitation, we retrieve the occupation information from the last employment spell of the SIAB or the GSOEP, in case no consent for the SIAB linkage was given. If entry into the labor market occurs after cohabitation, we consider the first observed occupation in either data set. For these individuals (about 3 % of the sample, mainly students), we assume that upon cohabitation, they know which occupation they will work a few years later. This leaves us with 1,476 couples. The next part describes the variables relevant for matching.

[3] We use the most recent wave (2018) and conduct a robustness check in which we average over the last two waves (2012 and 2018).

[4] In the marriage market literature, it is common to analyze marriage instead of cohabitation because marriage is generally the only information available (Dupuy and Galichon, 2014; Ciscato, Galichon, and Goussé, 2020). Instead, we focus on the time of cohabitation (like Calvo, Lindenlaub, and Reynoso, 2024) which allows us to measure occupations at a time when household specialization plausibly does not play an important role yet. Furthermore, we can thereby include couples in our analysis who never get married, which is becoming increasingly common.

Table 1: Summary statistics - matching variables

	Men	Women
Panel A: Individual level		
Age at cohabitation	30.69	27.54
	(7.65)	(5.72)
Years of education	12.53	12.77
	(2.79)	(2.80)
Spouses had the same occupation	0.14	0.14
	(0.35)	(0.35)
Panel B: Occupation $\times$ gender level		
Earnings	1,041.43	781.54
	(321.82)	(223.53)
Part-time potential	0.14	0.53
	(0.11)	(0.14)
Schedule regularity	-0.25	0.17
	(1.22)	(1.42)
Work meaning	2.66	2.72
	(0.11)	(0.15)
Observations	1,476	1,476

Notes: Panel A reports matching variables at the individual level while panel B reports gender-occupation-specific matching variables. Part-time potential also differs by year. Earnings refer to lifetime full-time earnings and are reported in thousands of euros.

3.3 Matching variables

We have seven main matching variables - dimensions spouses sort on - which are presented in Table 1. At the individual level, we include the demographic variables age and education. In the first year of cohabitation, men are on average 31 and women 28 years old. Individuals have on average between 12 and 13 years of education (including years of schooling and vocational training).[5] Our remaining matching variables are occupation (at the individual level) and job characteristics.

3.3.1 Job characteristics

We are interested in whether individuals take *future* job characteristics into account when deciding on a partner. Since we do not observe expectations or career ambition (Bursztyn, Fujiwara, and Pallais, 2017) directly, we impute gender-occupation-specific averages of amenities at the 2-digit occupation level (DeLeire and Levy, 2004; Dupuy and Galichon, 2022).[6] We interpret these averages as the expected future job characteristics that individuals observe at the time of matching. Unlike realized job characteristics measured later in the partnership, this measure is not mechanically affected by within-couple choices.

We consider the following job characteristics and depict descriptive statistics for our estimation sample in Table 1.

Lifetime full-time earnings. Earnings are highly relevant for inequality within and between couples and have, therefore, received ample attention in the literature on marriage matching (e.g., Eika, Mogstad, and Zafar, 2019; Chiappori, Fiorio, et al., 2022). We focus on full-time lifetime labor earnings to avoid a mechanical correlation with the part-time rate.[7] Specifically, we regress deflated full-time annual labor earnings on year fixed effects and a polynomial of age by occupation and gender. The sum of the predicted earnings between age 25 and 50 constitutes our earnings measure (Almar et al., 2025). Earnings are expressed in 2015 EUR. On average, men's expected full-time lifetime earnings (1.04 million EUR) are higher than women's (0.78 million EUR).

[5]This level of education corresponds to the ISCED 3 for the International Standard Classification for Education.

[6]We visualize the average amenities by gender for a subset of occupations in Figure A.1.

[7]Wages are right-censored in the IAB at the threshold that limits the amount individuals pay for social security contributions. We use the imputation methods for wages above this threshold based on Dustmann, Ludsteck, and Schönberg (2009) and Card, Heining, and Kline (2013) as provided by the IAB (Stüber, Dauth, and Eppelsheimer, 2023).

Part-time potential. An important dimension of occupational flexibility is the possibility to work part-time, specifically for women (Wiswall and Zafar, 2018). We proxy this job characteristic by the share of individuals who are working part-time in the year of cohabitation, occupation, and gender, again using the SIAB. On average, women in our sample work in occupations where every second woman works part-time, while the average for men is 14%.

Schedule regularity. An important amenity is the regularity of the work schedule. Mas and Pallais (2017) and Bell (2020) document strong (female) preferences for schedule regularity in the labor market. We use four questions and perform a Principal Component Analysis on the variables *on-call duties, work on the weekend, day shifts*, and *unpaid overtime work* in the BIBB/BAuA Employment Survey. We account for gender differences within occupations by computing the first principal component score by occupation and gender (see Appendix Section A.1 for more details on calculation).

Work meaning. Work meaning is a relevant part of the non-monetary remuneration of jobs (De Schouwer and Kesternich, 2025). While preferences for work meaning are heterogeneous in the population (De Schouwer, Gsottbauer, et al., 2025), the feeling of doing a job that is important is particularly relevant as it might contribute to job satisfaction and to feeling as an important part of society (Cassar and Meier, 2018). We rely on a question from the BIBB *'How often do you feel that your job is important?'* measured on a four-item scale from never (coded as 0) to frequently (coded as 3). We calculate averages separately by occupation and gender. Most men and women work in occupations in which people consider their work to be important, where perceived work meaning is slightly larger for women.

To understand how the matching variables vary in our estimation sample, we report correlations between those variables separately for women and men in Appendix Tables A.3 and A.4. We find that earnings strongly and positively correlate with education and schedule regularity, whereas the correlation with meaning is less strong but positive. In contrast, part-time potential is negatively correlated with earnings. In the regression, these associations remain (see Table A.5). Furthermore, we document interesting gender differences in other amenities. For instance, a higher part-time potential is associated with more meaning for men and women, but for schedule regularity, we find negative (positive) associations for women (men). Also, in line with De Schouwer and Kesternich

(2025), we find a negative relationship between work meaning and schedule regularity for women.

In a robustness check, we compute occupation-specific averages only. In other robustness analyses, we calculate percentile ranks for schedule regularity and work meaning (following Calvo, Lindenlaub, and Reynoso, 2024) and average over two survey waves of the BIBB.

3.3.2 Correlations between partners' characteristics

As a starting point to uncover who marries whom, we calculate pairwise correlations between partners' characteristics (Table 2). This provides an intuitive view of how attributes co-vary within couples. We find positive correlations on the diagonal for all sorting dimensions, where correlation coefficients range from 0.71 (age) to 0.14 (work meaning). The off-diagonal correlations also reveal several relevant patterns, e.g., a high correlation between education and earnings (0.35 and 0.36). However, this approach does not take the correlation between attributes within individuals into account. It remains unclear whether the positive correlation of spouses' schedule regularity is based on sorting on this amenity or whether it is driven by sorting on education, which strongly correlates with schedule regularity. In contrast, with the matching model introduced in the last section, we can estimate the relevance of characteristics for couples' surplus conditional on the other characteristics.

Table 2: Pairwise correlation coefficients between partners' characteristics

	Women					
Men	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning
Age	0.71***	-0.03	0.02	-0.01	0.06**	0.01
Education	0.08***	0.52***	0.36***	-0.11***	0.24***	0.06**
Earnings	0.11***	0.35***	0.34***	-0.14***	0.24***	0.09***
Part-time potential	-0.01	-0.00	-0.06**	0.17***	-0.05*	0.03
Schedule regularity	0.06**	0.24***	0.22***	-0.09***	0.24***	0.03
Work meaning	0.06**	0.12***	0.11***	0.01	0.05**	0.14***

*Notes: Pairwise correlation coefficients for partners' matching variables. Number of observations: 1,476. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. *** significant at 1%, ** at 5% and * at the 10% level.*

Additionally, the partners' job characteristics might be positively correlated because partners frequently meet through work or education. In our sample, 14 % of all spouses worked in the same occupation (2-digit level) at the time they started cohabiting. We include the occupation code as a categorical matching variable in the matching model such that sorting on job characteristics in the matching function is identified net of within-occupation matching.

4 Results

We estimate the equilibrium matching model and present the estimated affinity matrix A in Table 3. As discussed in Section 2, the matrix measures the mutual attractiveness of partners' characteristics, while taking into account the other characteristics and their marginal distribution. We standardize all variables to ease the comparison of the magnitude of coefficients across characteristics. Hence, the element i, j of the affinity matrix measures the change in the marginal gain or loss in joint utility from a one standard deviation increase in the man's attribute i as the woman's attribute j increases by one standard deviation.

In line with the literature, we find strong positive assortative matching with respect to age, education, and earnings (e.g., Chiappori, Ciscato, and Guerriero, 2024). For instance, when increasing the age of one partner by one standard deviation, the marginal effect of the age of the other partner on joint utility increases by 1.56. This is in line with Ciscato, Galichon, and Goussé (2020) who find age coefficients of 1.14 and 2.17 for unmarried and married couples, respectively. For education, we find a diagonal coefficient of 0.53, which is very close to the estimates by Dupuy and Galichon (2014) (0.56) and only slightly below the estimates by Ciscato, Galichon, and Goussé (2020) (0.66 and 0.82, respectively).

Our key contribution is that we examine assortative matching on non-wage amenities. Conditional on occupation, we find positive and significant coefficients for part-time potential and schedule regularity, revealing positive assortative matching along these dimensions. Interestingly, our measure of mutual attractiveness for part-time potential (0.56) is even larger than for earnings (0.35) and education (0.53). These results indicate complementarities in marital surplus along part-time potential and schedule regularity.

By contrast, the work meaning attribute is associated with only a small positive coefficient of 0.04, which is not statistically significant. This suggests that complementarities in marital surplus along this dimension are limited relative to other job characteristics. This is consistent with work meaning

Table 3: Estimated affinity matrix

	Women						
Men	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning	Occupation
Age	1.56***	-0.08	0.01	-0.02	-0.00	-0.03	
	(0.07)	(0.06)	(0.07)	(0.11)	(0.07)	(0.07)	
Education	0.06	0.53***	0.20***	0.02	-0.04	0.00	
	(0.04)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)	
Earnings	0.17**	0.15*	0.35***	0.06	-0.07	0.07	
	(0.08)	(0.08)	(0.10)	(0.15)	(0.10)	(0.09)	
Part-time potential	0.18**	0.12	0.33***	0.56***	-0.05	-0.08	
	(0.08)	(0.08)	(0.10)	(0.16)	(0.10)	(0.09)	
Schedule regularity	-0.08*	-0.01	-0.25***	-0.03	0.15***	-0.03	
	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)	
Work meaning	-0.07*	-0.02	-0.01	-0.06	-0.07	0.04	
	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)	
Occupation							1.10***
							(0.09)

*Notes: Estimated affinity matrix indicating mutual attractiveness of men's and women's characteristics. Number of observations: 1,476. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. Standard errors in parentheses. *** significant at 1%, ** at 5% and * at the 10% level.*

being less directly relevant for household production. Alternatively, our occupation-level measure of work meaning may capture less variation that is salient at the time of matching.

Occupation is a relevant matching attribute: working in the same occupation increases marital surplus by 1.10 units. Because the other estimated coefficients are conditional on within-occupation matching, they are unlikely to reflect purely mechanical same-occupation sorting. Broader meeting effects through workplaces, industries, education tracks, or local labor markets are, however, not fully ruled out.

The off-diagonal elements of the affinity matrix reveal gender-specific differences in matching preferences. Older (younger) women tend to match with high (low)-earning men, while we do not find a relation of male age and female earnings. Interestingly, we find that men with less (more) regular schedules tend to match with high-earning (low-earning) women, indicating substitutability in marital surplus between women's earnings and men's schedule regularity. The latter might be because higher earnings make it easier to pay for childcare, in line with the household production channel.

Robustness checks. To test the sensitivity of our results under different specifications, we first re-estimate the affinity matrix using occupation-specific averages of earnings and non-wage amenities rather than using gender-occupation-specific information. This allows for more precise measures and assumes that men and women working in the same occupation face the same potential amenities on average. Overall, the results remain largely stable, with minor changes in magnitude (see Table C.7). The main exception is part-time potential: the on-diagonal coefficient is about four times smaller, and off-diagonal coefficients with age and earnings are reduced by roughly half. That we see the biggest differences for part-time potential is not surprising given that part-time rates differ strongly between men and women (as we have seen in Table 1).

In another robustness analysis, we use the percentile rank when calculating gender-occupation-specific schedule regularity and work meaning (following Calvo, Lindenlaub, and Reynoso, 2024). This is more robust against potential outliers. This yields very similar results (Appendix Table C.8).

Third, we use different survey years of the BIBB/BAuA Employment Survey, which is used for schedule regularity and work meaning. This accounts for potential changes in amenities at the occupation level over time. We average the amenity values by occupation and gender across the two available waves (2012 and 2018 instead of only 2018).[8] Appendix Table C.9 reveals that the results are qualitatively unchanged, with the coefficients getting only slightly lower.

5 Counterfactual simulations

To investigate the contribution of marital sorting to between-household inequality (Eika, Mogstad, and Zafar, 2019; Ciscato and Weber, 2020) and the role of matching on amenities, we compute Gini coefficients for simulated hypothetical matchings under counterfactual preferences.

We use two different measures of couple-level compensation. We start by only considering earn-

[8] If one wave has missing values for any amenity for any occupation, we use the information of the other wave.

ings by adding up the spouses' lifetime full-time earnings imputed on the occupation $\times$ gender level as before. Second, acknowledging that an important part of remuneration for a job is non-wage amenities, we also use a measure of total compensation. Gender-specific total compensation is computed as the sum of earnings and the monetary valuation of amenities (similar to De Schouwer and Kesternich, 2025):

$$\text{total compensation}_g = earnings_{o,g} \cdot \left(1 + \sum WTP_g^a \times a_{o,g}\right) \tag{4}$$

where WTP_g^a denotes gender-specific willingness to pay for amenity a, expressed as a fraction of earnings, and $a_{o,g}$ captures the level of amenity a for gender g in occupation o. In a 'back-of-the-envelope' manner, we use the WTP_g^a coefficients from previous literature on willingness to pay for amenities estimated using discrete choice experiments. Because these willingness-to-pay inputs come from studies in the US and the Netherlands and because we binarize continuous amenity measures, the resulting magnitudes should be interpreted as illustrative rather than exact. We provide an overview of willingness to pay estimates from previous literature, a description of how we selected these values, and a description of how we binarized our continuous amenity measures to calculate total compensation in Appendix B.

We compare the Gini using household compensation—the sum of spouses' total compensation—over three scenarios, in which we change marital preferences: In the *baseline* scenario, preferences are as estimated in the affinity matrix, and the matching probabilities $\pi_{\hat{A}}(x, y)$ are therefore close to the empirical moments. Under *random matching*, couples do not consider any characteristics of their potential partner and match randomly, i.e., every individual has an equal probability of matching with any potential different-sex spouse. Finally, in the scenario *no amenities matching*, individuals no longer take amenities into account when selecting a partner. They therefore match on demographics, earnings, and occupation, but no longer on any amenities, which corresponds to setting all amenities-related entries in A to zero.

We present the results in Table 4. The first row in Panel A reports a Gini coefficient of 14.03 which is slightly below what Bönke, Corneo, and Lüthen (2015) find for individual-level lifetime earnings of men in Germany (between 16.6 and 21.6). This is expected, since we use a couple-level measure and

Table 4: Counterfactual Gini coefficients

Scenario	**Gini coefficient**	Δ% **Baseline**
Panel A: Earnings		
Baseline	14.03	–
Random matching	12.32	-12.2%
No amenities matching	14.50	+3.4%
Panel B: Total compensation		
Baseline	15.23	–
Random matching	13.34	-12.4%
No amenities matching	15.74	+3.3%

Notes: In panel A, we report Gini coefficients scaled from 0 to 100 based on (imputed) couple-level lifetime full-time earnings over different scenarios. In panel B, we use total compensation, which includes the valuation of amenities (see equation 4), instead of earnings. Under the "Baseline" scenario, couples match based on estimated marriage patterns while "Random matching" refers to partners pairing randomly. "No amenities matching" refers to counterfactual matching patterns in which individuals do not match on non-wage amenities, but still take the other matching variables into account. Number of observations: 1,476. The last column reports the percentage change relative to the baseline scenario in the respective panel.

do not account for within-occupation earnings heterogeneity and realized part-time work, which all likely reduces measured inequality.

We find that inequality between couples is larger when we consider the valuation of non-wage amenities: the Gini coefficient is 15.23 in the baseline scenario in the first row of Panel B. This aligns with studies looking at the contribution of non-wage amenities to inequalities on the labor market (Maestas et al., 2023).

The main point of interest is how the inequality measures differ across counterfactual scenarios. For total compensation, under 'Random matching', the Gini is about 1.9 points or 12.4% lower than 'Baseline' indicating that marriage-market sorting contributes substantially to between-household inequality (confirming the results by Ciscato and Weber, 2020). In contrast, if individuals sort on demographics and earnings, but not amenities, the Gini is about 0.5 points larger than in the baseline scenario. That corresponds to an increase of 3.3% for total compensation and 3.4% for lifetime earnings. Given the imported willingness-to-pay inputs and the discretization of amenity measures, these magnitudes should be viewed as illustrative. Hence, the fact that individuals match on amenities has a small dampening effect on marriage-market-related between-household inequality.

Sorting on earnings becomes more pronounced when individuals no longer sort on amenities. At the same time, off-diagonal elements of the affinity matrix mitigate positive assortative matching on earnings. For example, when amenities are taken into account, low-earning women are more likely to match with men who have high schedule regularity – a trait that is positively correlated with higher earnings.

6 Discussion and conclusion

We examine the relevance of non-wage job characteristics for marriage sorting. Our results show strong positive assortative matching with respect to schedule regularity and part-time potential of jobs. This implies that joint surplus is maximized if high-schedule regularity (part-time potential) men match with high-schedule regularity (part-time potential) women and vice versa, conditional on earnings, education, and the other considered variables. These patterns indicate complementarities in marital surplus along these dimensions. For work meaning, we do not find statistically significant complementarities. This is consistent with household production being an important component of marital surplus, as work meaning is likely less relevant for household production, whereas alternative mechanisms—such as preferences for similarity—would be expected to generate assortative matching along this dimension as well.

Interestingly, off-diagonal results show substitution patterns between some partners' characteristics. For example, women in high-earning occupations tend to have a partner with low schedule regularity. This could be due to affordability of childcare.

Our paper shows that between-household inequality is understated when researchers ignore job amenities. Moreover, our illustrative counterfactual calibration indicates that while marital sorting generally increases between-household inequality, sorting on non-wage amenities in particular has a dampening effect.

The documented positive sorting on schedule regularity and part-time potential is consistent with a setting in which these amenities contribute to joint household decisions, including a more gender-balanced division of household work. However, partners with irregular schedules and small part-time potential tend to match together, and thus may have less time to devote to household chores and child welfare. This should, for instance, be taken into account when designing childcare policies.

Future research could build on our results and analyze how amenities relate to couple outcomes like fertility or time use patterns. Similarly, it would be interesting to analyze how occupation choice is influenced by amenities-related marriage market opportunities. Both would require longer-running panel data and a dynamic model setup.

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Appendix

A Data

A.1 Measurement of amenities in the BIBB/BAuA sample

In the following, we describe our measurement of the amenities *schedule regularity* and *work meaning* (see section 3) in more detail. We rely on the Employment Survey of the BIBB/BAuA, which takes place every six years and asks questions on working conditions, non-wage amenities, and demographics.

Table A.1 displays the variables and coding of raw items we use to generate those amenities, while Table A.2 depicts summary statistics of these amenities by gender.

Work meaning relies on a single question, "How often do you feel that your job is important?", and is aggregated by occupation and gender, as an average over all working individuals in the sample. On average, the feeling that work is important does not differ much by gender.

For *schedule regularity*, we aim to generate a variable that measures how predictable/regular a schedule is. We reverse code *on-call duties, work on the weekend, unpaid overtime work* and aggregate it jointly with *day shift* by occupation and gender. We obtain the first principal component score of a PCA and report summary statistics of the items in Table A.2. Note that these are the averages across occupations and rely solely on the composition of the BIBB/BAuA sample. Differences in averages relative to the actual estimation sample can be due to compositional differences.

Note that the items changed slightly between the 2012 and 2018 waves. We use the most recent wave in our main specification and conduct a robustness check in which we average over both waves.

Table A.1: Overview of variables included from the BIBB surveys

Variable	Question	Answers	Coding
BIBB 2012			
On-call duties	Are you on standby duty or on-call duty?	Yes/No	1 if Yes
Work on the weekend	How many Saturdays/Sundays and public holidays a month do you work, on average?	XX Saturdays/Sundays and public holidays per month	1 if at least once
Day shifts	Are your working hours typically between 7 a.m. and 7 p.m.?	Yes/No	1 if Yes
Unpaid overtime work	How are you compensated for your extra work or your overtime?	by remuneration; by time off; by both; there is no compensation	1 if There is no compensation
Work meaning	How often do you feel that your work is important?	Often to never (4-point scale)	Average
BIBB 2018			
On-call duties	Have you agreed the following in your activity?	Standby duty; on-call duty, work on call, None of it	1 if standby or on-call duty
Work on the weekend	Do you normally work at least once a month on Saturdays/Sundays?	Yes/No	1 if Yes
Day shifts	Do you normally work between 7 and 19 o'clock?	Yes/No	1 if Yes
Unpaid overtime work	How is your overtime or extra work compensated?	by payment; through leisure time compensation; through both; there is no compensation	1 if There is no compensation
Work meaning	How often do you feel that your job is important?	Frequently; Sometimes, Rarely; Never	Average

Table A.2: Descriptive statistics on amenity measures, by gender

	Male	Female	Total
2012			
No on-call duties	0.76	0.86	0.81
	(0.14)	(0.08)	(0.12)
No work on the weekend	0.42	0.56	0.49
	(0.16)	(0.23)	(0.21)
Day shifts	0.74	0.76	0.75
	(0.18)	(0.15)	(0.17)
No unpaid overtime work	0.89	0.93	0.91
	(0.08)	(0.08)	(0.08)
1st principal component regularity	-0.31	0.41	-0.00
	(1.39)	(1.35)	(1.41)
Work meaning	2.67	2.64	2.66
	(0.11)	(0.23)	(0.18)
2018			
No on-call duties	0.77	0.84	0.80
	(0.15)	(0.13)	(0.14)
No work on the weekend	0.50	0.56	0.53
	(0.21)	(0.24)	(0.22)
Day shifts	0.73	0.77	0.75
	(0.18)	(0.16)	(0.17)
No unpaid overtime work	0.91	0.93	0.92
	(0.07)	(0.06)	(0.07)
1st principal component regularity	-0.27	0.34	-0.00
	(1.32)	(1.47)	(1.41)
Work meaning	2.68	2.65	2.66
	(0.13)	(0.21)	(0.17)

Notes: We report averages of non-wage amenities over occupations by gender from the BIBB/BAuA employment survey.

A.2 Descriptives

Table A.3: Pairwise correlation coefficients for women's characteristics

	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning
Age	1.00					
Education	0.04	1.00				
Earnings	0.07**	0.48***	1.00			
Part-time potential	-0.01	-0.14***	-0.48***	1.00		
Schedule regularity	0.11***	0.33***	0.66***	-0.20***	1.00	
Work meaning	0.04	0.06**	0.03	0.44***	0.05**	1.00

*Notes: Pairwise correlation coefficients for women's matching variables. Number of observations: 1,476. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. *** significant at 1%, ** at 5% and * at the 10% level.*

Table A.4: Pairwise correlation coefficients for men's characteristics

	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning
Age	1.00					
Education	0.03	1.00				
Earnings	0.07***	0.47***	1.00			
Part-time potential	-0.03	-0.02	-0.34***	1.00		
Schedule regularity	0.05**	0.32***	0.69***	-0.30***	1.00	
Work meaning	0.06**	0.16***	0.32***	0.15***	0.25***	1.00

*Notes: Pairwise correlation coefficients for men's matching variables. Number of observations: 1,476. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. *** significant at 1%, ** at 5% and * at the 10% level.*

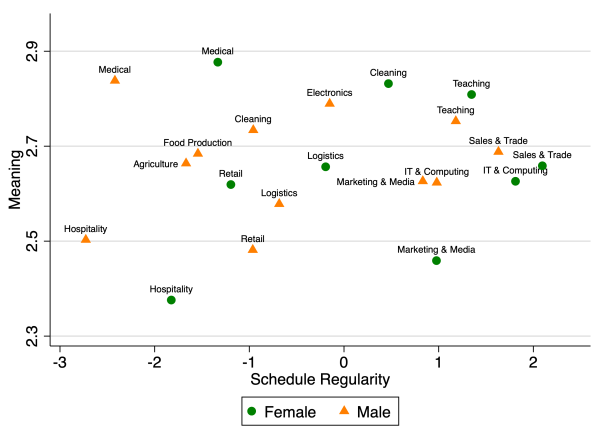
Table A.5: Regression of work meaning and schedule regularity on job characteristics

	Work meaning		Schedule regularity		Part-time potential	
	Women	Men	Women	Men	Women	Men
Age	0.03	0.04*	0.07***	0.00	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education	-0.03	-0.04	0.01	0.03	0.10***	0.19***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Log earnings	0.43***	0.37***	0.72***	0.61***	-0.67***	-0.49***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Part-time potential	0.63***	0.33***	0.19***	-0.08***		
	(0.03)	(0.03)	(0.03)	(0.02)		
Schedule regularity	-0.09***	0.10***			0.17***	-0.10***
	(0.03)	(0.03)			(0.02)	(0.03)
Work meaning			-0.07***	0.07***	0.46***	0.30***
			(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	1,476	1,476	1,476	1,476	1,476	1,476
R^2	0.291	0.185	0.427	0.458	0.485	0.260

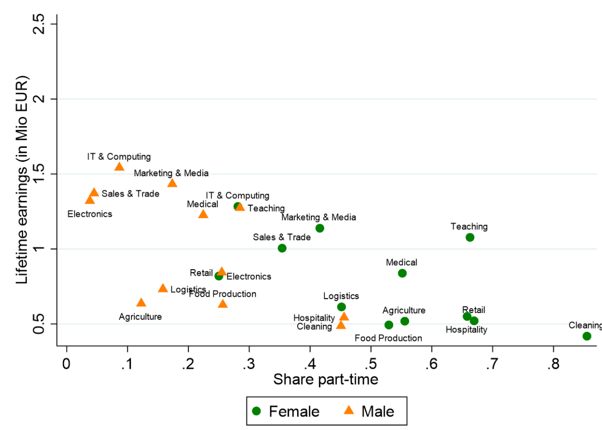
*Notes: OLS regression coefficients. All variables are standardized. Standard errors in parentheses. *** significant at 1%, ** at 5% and * at the 10% level.*

Figure A.1: Relationship between job characteristics for a subset of occupations

Panel (a): Work meaning and schedule regularity



Panel (b): Lifetime earnings and part-time potential



Notes: Panel (a) shows a subset of occupations and their associated gender-specific work meaning and schedule regularity. Panel (b) plots the average full-time lifetime labor earnings against the share of part-time workers of a subset of occupations by gender.

B Counterfactual simulations

To compute the total compensation in Equation 4, we use coefficients from the previous literature on willingness to pay for amenities estimated using discrete choice experiments. We document estimates over different studies in Table B.6. As definitions of variables differ over studies, we select valuations that are closest to the definitions in our data. If the valuations were estimated using different subsamples (e.g., women with and without children), we took the average of these valuations. For men (and women), we set the valuations to 0.019 (0.073) for part-time potential, following Wiswall and Zafar (2018) as it is the only study considering a part-time option instead of an actual part-time job. We follow Maestas et al. (2023) for schedule regularity, resulting in a coefficient of 0.085 (0.093). For work meaning, we use 0.047 (0.079) based on estimates byDe Schouwer and Kesternich (2025).

This part of the analysis should be interpreted in a 'back-of-the-envelope' manner, because discrete choice experiments treat amenities as binary. Thus, we discretize our continuous amenity measures as follows:

- **Part-time potential:** We keep it as it is, because it ranges between 0 and 1, and indicates the share of people working part-time in an equilibrium labor market.
- **Schedule regularity:** Classified as *regular* if the first principal component of schedule-related variables (quick availability, weekend shifts, day shifts, unpaid overtime) is above zero, and as *irregular* otherwise. This corresponds to a split at the mean, ensuring comparability across the sample.
- **Work meaning:** Classified as *meaningful* if the reported average meaning score is above 2.5. Values of 0–2 correspond to "never" to "sometimes meaningful," while 3 indicates "frequently meaningful."

Table B.6: Estimates of job amenity valuations using discrete-choice experiments

Amenity	Authors	Amenity definition	Sample	Estimates: Women	Estimates: Men
Schedule Regularity	**Maestas et al. (2023)**	**Set own schedule vs Schedule set by manager**	**US (AWCS)**	**0.093 (0.008)**	**0.085 (0.010)**
	De Schouwer and Kesternich (2025)	*Schedule adaptability:* Whether individuals can determine their own schedule, or whether their schedule is set by their employer.	Netherlands (LISS)	No children: 0.085 (0.010) Children: 0.096 (0.010)	No children: 0.056 (0.007) Children: 0.060 (0.007)
	Mas and Pallais (2017)	*Flexible schedule:* You can make your own schedule.	US (UAS)	All: 0.025 (0.004)	
Part-time	**Wiswall and Zafar (2018)**	***Part-time option:* Having the option of part-time work available.**	**US (NYU students)**	**0.0729 (0.0161)**	**0.0109 (0.024)**
	De Schouwer and Kesternich (2025)	*Part-time:* Working 32-hour work week.	Netherlands (LISS)	No children: -0.013 (0.013) Children: 0.041 (0.013)	No children: -0.051 (0.009) Children: -0.077 (0.010)
	De Schouwer and Kesternich (2025)	*Part-time:* Working 20-hour work week.	Netherlands (LISS)	No children: -0.044 (0.015) Children: -0.024 (0.010)	No children: -0.167 (0.016) Children: -0.195 (0.013)
Work meaning	**De Schouwer and Kesternich (2025)**	***Work meaning:* "The ability to positively impact one's community or society through work."**	**Netherlands (LISS)**	**No children: 0.090 (0.009) Children: 0.067 (0.009)**	**No children: 0.048 (0.006) Children: 0.045 (0.006)**
	Maestas et al. (2023)	*Community service opportunities:* The job frequently provides opportunities to make a positive impact on your community or society.	US (AWCS)	0.033 (0.009)	0.039 (0.010)

Notes: Estimates of job amenity valuations as a fraction of earnings. Estimates are reported with standard errors in parentheses where available. The estimates we use for our counterfactual simulations are in bold.

C Robustness

Table C.7: Affinity matrix - At occupation level

Men	Women: Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning	Occupation
Age	1.57***	-0.08	-0.01	-0.03	0.01	-0.02	
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	
Education	0.07	0.57***	0.16***	0.08*	-0.06	-0.02	
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	
Earnings	0.13**	0.20***	0.29***	0.03	-0.13*	0.06	
	(0.06)	(0.06)	(0.08)	(0.06)	(0.08)	(0.06)	
Part-time potential	0.09*	0.10*	0.15**	0.13***	-0.07	-0.02	
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	
Schedule regularity	-0.07	-0.07	-0.16**	0.01	0.18***	-0.02	
	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)	(0.05)	
Work meaning	-0.03	-0.03	-0.06	-0.07**	-0.04	0.05	
	(0.04)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)	
Occupation							1.21***
							(0.09)

*Notes: This table replicates Table 3 using occupation-level measures for earnings, part-time potential, schedule regularity, and work meaning instead of gender- and occupation-level measures. This increases the number of couples for which we can impute valid job characteristics. Number of observations: 1,674. Education and age are at the individual level. Standard errors in parentheses. *** significant at 1%, ** at 5% and * at the 10% level.*

Table C.8: Affinity matrix – Percentile rank

Men	Women						
	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning	Occupation
Age	1.56***	-0.08	-0.01	-0.04	0.01	-0.01	
	(0.07)	(0.06)	(0.07)	(0.11)	(0.08)	(0.06)	
Education	0.06	0.53***	0.20***	0.01	-0.04	0.01	
	(0.04)	(0.04)	(0.06)	(0.08)	(0.06)	(0.04)	
Earnings	0.18**	0.14*	0.34***	0.07	-0.05	0.05	
	(0.08)	(0.08)	(0.10)	(0.15)	(0.11)	(0.08)	
Part-time potential	0.19**	0.12	0.31***	0.57***	-0.01	-0.09	
	(0.08)	(0.08)	(0.10)	(0.16)	(0.11)	(0.08)	
Schedule regularity	-0.09**	-0.01	-0.27***	0.01	0.16***	-0.00	
	(0.04)	(0.04)	(0.05)	(0.08)	(0.06)	(0.04)	
Work meaning	-0.06	-0.01	-0.00	-0.10	-0.08	0.05	
	(0.04)	(0.04)	(0.05)	(0.07)	(0.05)	(0.04)	
Occupation							1.10***
							(0.09)

*Notes: This table replicates Table 3 using the percentile rank for the amenities: schedule regularity and meaning. Number of observations: 1,476. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. Standard errors in parentheses. *** significant at 1%, ** at 5% and * at the 10% level.*

Table C.9: Affinity matrix - 2012-2018 BIBB data

	Women						
Men	Age	Education	Earnings	Part-time potential	Schedule regularity	Work meaning	Occupation
Age	1.59***	-0.08	0.02	-0.03	0.00	0.00	
	(0.07)	(0.06)	(0.07)	(0.11)	(0.07)	(0.06)	
Education	0.04	0.55***	0.19***	0.01	-0.05	-0.00	
	(0.04)	(0.04)	(0.05)	(0.08)	(0.05)	(0.04)	
Earnings	0.16**	0.16**	0.28***	0.03	-0.04	0.07	
	(0.08)	(0.07)	(0.09)	(0.15)	(0.09)	(0.08)	
Part-time potential	0.15**	0.14*	0.27***	0.43***	-0.05	-0.10	
	(0.07)	(0.07)	(0.08)	(0.14)	(0.09)	(0.08)	
Schedule regularity	-0.08*	-0.03	-0.23***	0.01	0.15***	-0.04	
	(0.05)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)	
Work meaning	-0.04	-0.06*	0.03	-0.00	-0.07*	0.02	
	(0.04)	(0.03)	(0.04)	(0.06)	(0.04)	(0.04)	
Occupation							1.17***
							(0.09)

*Notes: This table replicates Table 3 using two waves of data (2012 & 2018) for the amenities: schedule regularity and meaning. When constructing these variables, we retain inferred values in cases where averaging across waves is not feasible but at least one wave provides valid information, thereby increasing the number of observations: 1,586. Education and age are at the individual level, whereas earnings, part-time potential, schedule regularity, and work meaning are gender- and occupation-specific. Standard errors in parentheses. *** significant at 1%, ** at 5% and * at the 10% level.*

Table C.10: Counterfactual Ginis – Robustness

Scenario	Gini coefficient	Δ% Baseline
At occupation level		
Panel A: Earnings		
Baseline	13.94	–
Random matching	12.30	-11.8%
No amenities matching	14.60	+4.8%
Panel B: Total compensation		
Baseline	15.14	–
Random matching	13.33	-12.0%
No amenities matching	15.84	+4.6%
Percentile Rank		
Panel A: Earnings		
Baseline	14.03	–
Random matching	12.32	-12.2%
No amenities matching	14.48	+3.2%
Panel B: Total compensation		
Baseline	15.28	–
Random matching	13.39	-12.4%
No amenities matching	15.76	+3.2%
2012-2018 BIBB average		
Panel A: Earnings		
Baseline	14.20	–
Random matching	12.46	-12.2%
No amenities matching	14.56	+2.5%
Panel B: Total compensation		
Baseline	15.42	–
Random matching	13.49	-12.5%
No amenities matching	15.81	+2.6%

These stacked tables replicate Table 4 by calculating all amenities at the occupation level (top table), using percentile ranks for schedule regularity and work meaning (middle table), and using information from both the 2012 and 2018 waves of the BIBB data (bottom table).