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Abstract

We study marital sorting using a novel dataset from a marriage matching platform, which uniquely records a rich set of pre-marital attributes, including preferences for children and for the division of housework and childcare. Unlike census or post-marital surveys, all characteristics are collected prior to matching and validated using official documents, yielding clean measures of preferences uncontaminated by post-marital coordination. Applying a multidimensional matching framework to twelve attributes, we find strong positive assortative matching across all dimensions. Age is the most salient trait, but preferences for children are the second most important—exceeding education—a pattern largely invisible in standard data. Preference measures play a distinct role in the matching process: they exhibit limited cross-attribute interactions with sociodemographic and anthropometric characteristics, in contrast to the pervasive interactions among those attributes. A low-dimensional factor representation shows that preferences for children constitute a separate and salient margin of sorting. Using the staged structure of the platform, we further show that assortative matching along different dimensions emerges at distinct points in the dating process: sorting by age and income is already present at the initial Application stage, whereas sorting by preferences for children becomes robust only at later stages of relationship formation, reflecting selective continuation rather than sorting at the point of final agreement. A simple theoretical exercise demonstrates that ignoring preference-based sorting and assuming homogeneous preferences across couples leads to biased estimates of policy effects on subsequent household decisions.

Keywords: Marriage market, assortative matching, fertility preferences, multidimensional matching

JEL code: D13, J12, J13

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1 Introduction

Understanding how individuals sort into marriage is central to household economics and to the distributional consequences of household formation. Prior work documents strong positive assortative matching on education (Greenwood *et al.* 2014, Eika *et al.* 2019, Chiappori *et al.* 2025), age (Choo and Siow 2006), income (Chiappori *et al.* forthcoming), and other sociodemographic characteristics. However, much less is known about how individuals sort on preferences that directly govern household behavior—such as the desire to have children or the willingness to engage in housework and childcare—even though these preferences fundamentally shape subsequent household decisions, including fertility, labor supply, and within-household time allocation. [1] This gap primarily reflects data limitations: these preferences are usually unavailable in registry and census data, and even when surveys collect information on preferences, observations prior to marriage are rarely available. Existing evidence therefore provides limited guidance on whether and how pre-marital preferences contributes to observed assortative matching.

This paper brings new evidence to this question using a uniquely rich dataset with directly observed household-relevant preferences. Specifically, we analyze a novel dataset from IBJ, Japan's largest structured marriage matching platform. IBJ represents a non-negligible share of marriages in Japan: the data record over 10,000 confirmed engagements per year and about 3.3% of all new marriages in 2024. In addition to standard attributes used in the marriage market literature, such as sociodemographic characteristics (e.g., education, age, and income) and anthropometric measures (e.g., height and weight), the data include preferences for children and post-marital time allocation between market work and home. These preferences measures correspond directly to primitives that shape post-marital household decisions, letting us study marital sorting on theoretically first-order but rarely observed characteristics. Notably, all attributes and preferences are collected prior to matching. As a result, they are not shaped by post-marital intra-household coordination, which can contaminate survey measures from already-married couples commonly used in the literature. [2] For example, spouses may adjust labor supply, occupation, and income to exploit household specialization, and their reported preferences over children may converge as part of joint life planning. The pre-marital elicitation, therefore, makes our data an ideal setting for analyzing matching and sorting on a rich set of attributes, including preferences over fertility and time allocation.

Beyond measuring these novel pre-marital preferences, the IBJ data allow us to characterize how they relate to conventional anthropometric and sociodemographic attributes. Preferences for

[1] A growing body of work emphasizes that household behavior and matching should be analyzed jointly, rather than treating family formation as exogenous to intra-household decisions. While empirical studies of household behavior have made substantial progress, they typically condition on existing couples, abstracting from the selection processes that determine who forms a household with whom. In contrast, matching models highlight that partner selection is itself an endogenous process that shapes subsequent household behavior, bargaining power, and specialization. See, for example, the surveys by Chiappori and Salanié (2023), Chiappori and Low (2024), and Salanié (2024) for discussions of this integration and its importance for household economics.

[2] For instance, Chiappori *et al.* (2024), who use survey data on couples in Italy to analyze matching patterns, note that "an obvious caveat is that, since we observe couples a few years after marriage, some individual traits may have converged."

children and for the division of childcare and housework vary systematically with age, income, and education, yet their pairwise correlations with standard sociodemographic and anthropometric characteristics are generally modest, suggesting that these measures capture a distinct margin of heterogeneity rather than simply proxying for conventional traits. At the same time, strong correlations among conventional sociodemographic attributes indicate that assortativeness is best interpreted in a multidimensional framework that jointly accounts for these interactions.

Given these patterns, we apply the multidimensional matching framework of Dupuy and Galichon (2014) to study sorting on pre-marital preferences together with sociodemographic and anthropometric variables. With the rich set of variables, we do not restrict attention to a single attribute, unlike the approach in Choo and Siow (2006) and much of the subsequent literature (Chiappori and Low 2024). Specifically, we examine twelve observed or constructed attributes: education, age, income, occupational flexibility, height, weight, drinking, smoking, marital history, and preferences for housework, childcare, and children. This framework quantifies how multiple attributes and their interactions shape matching while accounting for correlations across attributes. Ignoring this multidimensional structure and focusing on a single trait can mislead inference when traits are strongly correlated.

The estimated affinity matrix, which summarizes whether each male–female attribute combination are complementary or substitutable, yields several findings. First, we find strong positive assortative matching among couples formed on the platform. Strikingly, all twelve attributes—sociodemographic, anthropometric, and preference measures—exhibit positive assortativeness, though this is not guaranteed ex ante. Because attributes are measured pre-match, these are clean sorting patterns rather than post-marital coordination artifacts. Age has the largest diagonal coefficient, consistent with prior work such as Chiappori *et al.* (2024). Remarkably, the second-largest diagonal coefficient is preferences for children — exceeding even education, which typically displays one of the strongest assortative patterns. This highlights that our rich pre-marital data uncover key sorting dimensions mostly invisible in standard datasets.

Second, the off-diagonal elements of the affinity matrix highlight the importance of cross-attribute interactions across genders. Among sociodemographic attributes (education, age, income) and anthropometric characteristics (height, weight), most interactions are statistically different from zero. Thus, a favorable trait in one dimension (e.g., higher income) tends to attract partners with stronger traits along other sociodemographic and anthropometric dimensions.

Occupational flexibility, constructed from occupations following Goldin (2014), plays a smaller role in sorting than other sociodemographic characteristics. Although sorting is positive on this dimension, the magnitude is small and interactions with other attributes are mostly absent. This pattern is informative in light of theoretical mechanisms: while occupational flexibility is increasingly recognized as relevant for within-household specialization or coordination after matching (Bang 2021, Erosa *et al.* 2022, Calvo *et al.* 2024), it need not be a primary margin of the partner selection stage.

Finally, interactions involving pre-marital child preferences show distinct patterns. Preferences for children are complements to childcare intentions: individuals willing to assume childcare responsibilities tend to match with partners who more strongly want children. By contrast, interactions between child preferences and most sociodemographic or anthropometric traits are small and statistically indistinguishable from zero, with age as an important exception. In particular, the interaction between male child preference and female age is negative, indicating that stronger fertility preferences are associated with younger partners along the female age dimension. By contrast, child preferences exhibit little interaction with education or income, suggesting that, despite the common view that education or income matter for childbearing, a desire for children does not systematically attract higher-education or higher-income partners, and highly educated or high-income individuals do not systematically attract partners with stronger child preferences. These striking patterns are only visible in a multidimensional matching framework with a rich set of attributes. A saliency decomposition analysis based on Dupuy and Galichon (2014) also confirms that child preferences are an important sorting margin with a role distinct from sociodemographic and anthropometric attributes.: three indices explain almost 90% of observable matching surplus, and child preferences dominate the third index (share 6%, above 20% of joint utility after accounting for cohort-restricted search).

We also evaluate whether standard unidimensional specifications provide reliable measures of assortative matching. We show that dimensionality matters: estimates derived from unidimensional specifications can diverge substantially from our fully multidimensional benchmark, particularly when attributes are correlated. By contrast, specifications that jointly include key demographic variables approximate the multidimensional benchmark more closely. These findings clarify when parsimonious models are informative and when they may instead lead to incomplete or distorted inference.

We further examine how preferences and sorting evolve over time using multi-year data. Few multidimensional matching studies can do this because most datasets provide either rich attributes or long panels, but not both. Using year-comparable normalization (Ciscato and Weber 2020), we find that sorting on age, height, weight, and child preferences remains strongly positive and stable over the decade; education sorting declines, income sorting remains broadly stable, and child-preference sorting remains persistently strong. These shifts suggest that the attributes valued in the marriage market have evolved over time, potentially reflecting changing social norms or economic conditions. Despite such dynamics, sorting on preferences for children remains strong and persistent, highlighting the importance of pre-marital preferences for children as a fundamental dimension of the marriage market.

While the time-series analysis characterizes how assortative matching at the Proposal stage evolves across years, it does not reveal when these patterns arise during dating. Our unique data address this because they record not only final match outcomes but also interactions at each stage of relationship formation, including initial meeting applications and subsequent decisions to enter exclusive commitments. Using the many-to-many framework of Fox (2018), we estimate assortativeness from Application to Proposal: age and income are robust from Application onward, marital history and child preferences emerge later, and other attributes are not robust. Overall, the stage-based analysis suggests that the assortative structure observed at the Proposal stage reflects selective continuation along a limited set of dimensions rather than the sudden emergence of sorting at the point of final commitment.

Finally, we present a simple theoretical model of fertility and labor supply to illustrate why recognizing sorting on pre-marital preferences — especially preferences for children — is important. Although conceptually natural, heterogeneous fertility preferences among households with the same observables are not commonly incorporated in theoretical or empirical structural models. This heterogeneity is often implicitly treated as inconsequential for average policy effects because aggregation is assumed to mask household-level differences. Our theoretical exercise shows otherwise: ignoring preference-based sorting generally overstates policy effects on fertility and labor supply. Given our empirical finding of significant sorting on child preferences, analyses that abstract from this heterogeneity are likely to yield policy predictions biased in magnitude, typically away from zero.

Related Literature. This paper contributes to three strands of literature. First and foremost, our work contributes to the literature on the marriage market. Since the seminal contribution of Choo and Siow (2006), there has been extensive structural empirical research on unidimensional sorting in the marriage market, primarily with respect to education (Chiappori *et al.* 2017). Given the importance of multiple attributes in shaping marital choices, we build on the quadratic affinity-matrix framework of Dupuy and Galichon (2014), which provides a flexible and empirically tractable model of multidimensional matching.[3] Several papers apply this multidimensional method to analyze marriage market sorting with different substantive focuses, such as same-sex couples (Ciscato *et al.* 2020) and changes in income inequality over time (Ciscato and Weber 2020).[4]

The closest related work is Chiappori *et al.* (2024), who use unique survey data from Italy to study multidimensional matching patterns with the model of Dupuy and Galichon (2014). Their key finding is that multidimensional matching indexes have predictive power for children's outcomes, highlighting the role of sorting in shaping intergenerational inequality. While our data do not include outcome variables, we observe a rich set of *pre-marital* characteristics, including preference

[3] The literature on multidimensional matching under transferable utility can be organized by modeling approach and the dimensions of sorting they emphasize. Index-based models study assortative matching on anthropometric and socioeconomic characteristics such as age, height, body mass index, wages, and education (Chiappori *et al.* 2012, 2020b), as well as on detailed educational programs and fields of study that proxy for earnings potential and work–life balance (Almar *et al.* 2025a). Bidimensional matching models focus on trade-offs between human capital and specific traits or constraints, including smoking behavior (Chiappori *et al.* 2018b), fertility (Low 2024), migration status (Ahn 2025), race (Chiappori *et al.* 2016), sexual orientation (Ciscato and Goussé 2024), and genetic characteristics (Zheng *et al.* 2025). Quadratic affinity-matrix models based on Dupuy and Galichon (2014) allow for richer interactions across multiple attributes, encompassing combinations of education, age, wages, anthropometric traits, health-related behaviors, personality traits, and household characteristics (Ciscato and Weber 2020, Chiappori *et al.* 2024, Ciscato *et al.* 2020). Finally, a growing macro-oriented literature embeds multidimensional sorting into search-and-matching environments with frictions to study equilibrium implications for marriage and labor markets (Lindenlaub 2017, Lindenlaub and Postel-Vinay 2023, Ciscato 2024, Calvo *et al.* 2024).

[4] Adda *et al.* (2025) use a related but distinct multidimensional matching framework to study how legal-status incentives affect the marriage decisions of natives and migrants in Italy.

measures tied to household decisions, that are directly relevant to analyzing sorting at the time of marriage. Our paper complements theirs by studying matching patterns using cleaner pre-marital attributes and by deriving implications for subsequent household decisions using these detailed preference measures.

In terms of data, our IBJ dataset is closest in spirit to datasets from online dating platforms. Several papers use data from online dating apps (Hitsch *et al.* 2010b, Ong and Wang 2015, Bapna *et al.* 2016, Egebark *et al.* 2021, Buyukeren *et al.* forthcoming) and from speed dating events (Fisman *et al.* 2006, Belot and Francesconi 2013) to study matching patterns and to draw implications for the marriage market. Compared with typical dating apps and speed dating environments, however, users on a marriage matching platform are substantially more selected into serious partnership formation due to screening processes and nontrivial financial costs. This selection allows us to speak more directly to preferences relevant to marriage, rather than casual dating. Moreover, unlike these datasets, user attributes in our data are verified through official documents, such as tax withholding forms and certified health checkup records, providing a high degree of reliability in analyzing matching patterns.[5] Also, our data record all information about match formation processes with timestamps, enabling us to identify the dating status and stage.

Second, we contribute to the literature linking matching models with subsequent household decisions. Recent surveys emphasize that understanding marriage market sorting and household behavior jointly is essential, as household formation and intra-household allocation are fundamentally interconnected processes (Chiappori and Salanié 2023, Chiappori and Low 2024, Salanié 2024). In line with this view, several papers explicitly model the equilibrium marriage market together with life-cycle decisions to analyze these interactions (Chiappori *et al.* 2018a, Gayle and Shephard 2019, Calvo *et al.* 2024, Reynoso 2024, Almar *et al.* 2025b, Calvo 2025, Almar and Ishihata 2026). Although our dataset does not contain direct measures of post-marital household behavior, our evidence of sorting not only on sociodemographic characteristics but also on preferences has important implications for this literature. In particular, models that link marriage market sorting to subsequent household decisions may need to incorporate such pre-marital preference-based sorting to generate accurate counterfactual policy predictions. For example, our findings of sorting on pre-marital preferences for children suggest that households with identical observables may nevertheless differ in underlying preference parameters. Our simple theoretical exercise shows that ignoring this heterogeneity and imposing preference homogeneity would overstate policy effects on fertility and labor supply. [6] [7]

Finally, we offer new insights into the literature on occupational flexibility and its implications for intra-household decisions. Goldin (2014) shows that a large gender wage gap arises in occupa-

[5] Lee (2016) is an exception in that her dataset allows the observation of eventual marriage outcomes and includes legally verified key background variables. Our data further contain a larger number of couples and span longer periods, as well as information on preferences for children and time allocation.

[6] See Doepke *et al.* (2023) for a survey of models of fertility.

[7] A large share of empirical structural models of fertility and labor supply assume homogeneous preferences for children conditional on observables (e.g., Bick 2016, Garcia-Moran and Kuehn 2017, Yamaguchi 2019, Kim *et al.* 2024, Jakobsen *et al.* 2024).

tions that reward long and inflexible hours, while Cortés and Pan (2019) demonstrate that alleviating women's time constraints at home through greater availability of substitutes for household production reduces this gap. Building on this work, recent studies emphasize that occupational choice and job flexibility shape intra-household specialization in labor supply, depending on the flexibility of each spouse, with important consequences for wages and career trajectories (Bang 2021, Erosa *et al.* 2022). Because households adjust labor supply differently based on spouses' relative flexibility, occupational flexibility is a potentially relevant dimension of partner selection. Despite this relevance, assortative matching based on occupational flexibility has received little empirical attention.[8] A closely related exception is Almar *et al.* (2025a), who study assortative matching in educational ambition, measured using expected initial wage levels and wage growth. They argue that collapsing labor market trajectories into a single earnings measure obscures heterogeneity in work–life balance that is relevant for family formation, and show that career paths with higher expected wage growth are negatively associated with various flexibility measures. Our paper complements this literature by examining matching patterns along this dimension. Although we find that sorting on occupational flexibility is modest, documenting these patterns helps clarify the extent to which couples sort on flexibility prior to making joint intra-household decisions.

The remainder of the paper is organized as follows. Section 2 describes our IBJ data and institutional setting. Section 3 presents the multidimensional matching models and econometric approach. Section 4 reports estimation results, Section 5 discusses implications for household-economic models, and Section 6 concludes.

2 Data

This section describes the IBJ data and institutional environment and presents summary statistics. This section also serves two purposes: to establish external validity and to document novel descriptive patterns in pre-marital preferences that motivate our structural analysis. Subsection 2.1 introduces the IBJ marriage agency platform and its institutional features. Subsection 2.2 outlines the matching process and dating stages through which engagements are formed. Subsection 2.3 presents summary statistics for matched couples in 2024 used in the main estimation. Subsection 2.4 reports correlations between preference measures and other observed attributes. Subsection 2.5 documents changes in the characteristics and preferences of matched users between 2015 and 2024.

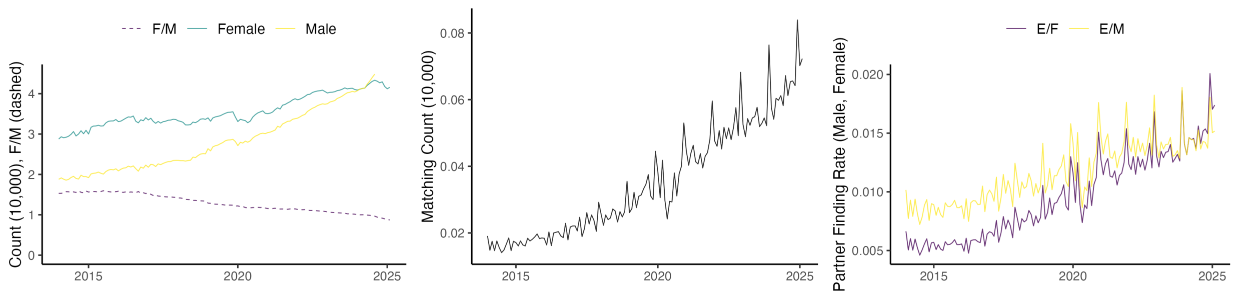
2.1 A Marriage Agency Platform

IBJ is a structured marriage-matching platform designed for long-term partnerships through a highly intermediated process. Unlike typical dating apps with open-ended, user-initiated interaction, IBJ imposes strict entry requirements, including document checks, health certification,

[8] A related literature examines assortative matching by occupation or industry (e.g., Kalmijn 1994). This work typically focuses on occupational titles rather than characteristics of occupations — such as flexibility, schedules, or career dynamics — that are central to intra-household coordination.

and upfront and ongoing fees. Users are matched through consultant-mediated proposals, and confirmed engagements require bilateral agreement. The platform follows a one-to-one rule and prohibits concurrent engagement. This design selects users actively seeking committed relationships and discourages casual participation, making the platform well suited for studying search and matching dynamics in a controlled, high-stakes environment.[9]

Macro Trends The IBJ platform has grown substantially in both user participation and matches. As Figure 1 shows, active users rose steadily from 2014 to 2025, with especially sharp male-side growth after 2020. This gender-specific expansion lowered market tightness (the female-to-male ratio), changing the matching environment. Engagements also rose markedly, especially after 2020. In 2024, IBJ facilitated over 10,000 engagements, accounting for 3.3% of marriages in Japan.[10] This coverage—especially for a high-verification, high-intent platform—offers an unprecedented view of modern partner search and formation.



(a) Female F, Male M, and tightness $(\frac{F}{M})$

(b) Engagement E

(c) Partner Finding Rate $(\frac{E}{F}, \frac{E}{M})$

Figure 1: Trends in key variables, 2014–2025

Note: See Otani (2025).

Market Coverage Figure 2 compares the joint distribution of matched IBJ couples with national benchmarks and shows systematic coverage differences. Relative to Vital Statistics (VS, *Jinko Dotai Chosa*), in Panel (a), IBJ engagements are concentrated among older couples, with greater mass in higher-age cells. This matches the platform's positioning toward later entrants to the marriage market rather than the full population of newly married couples.

Similarly, in Panel (b), compared with the National Fertility Survey (NFS, *Syussei Doko Kihon Chosa*), IBJ couples are more highly educated: the education-by-education matrix has larger shares in higher education categories for both genders and smaller shares in lower categories.

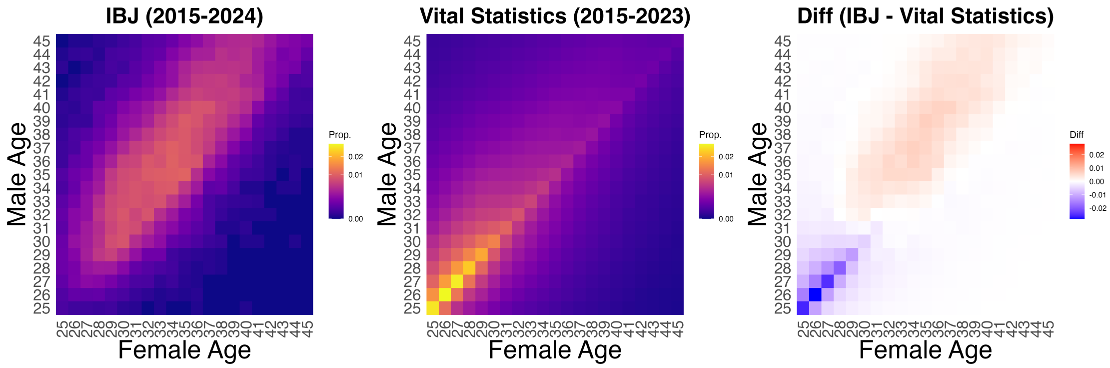
[9] Appendix A.1 provides a detailed comparison of the IBJ platform data with datasets used in recent related literature, highlighting the unique advantages of observing rich pre-marital attributes, unmatched users, and stage-by-stage matching outcomes.

[10] Approximately 50% of engagements among IBJ users occur within the platform, while the remaining 50% result from relationships formed outside the platform.

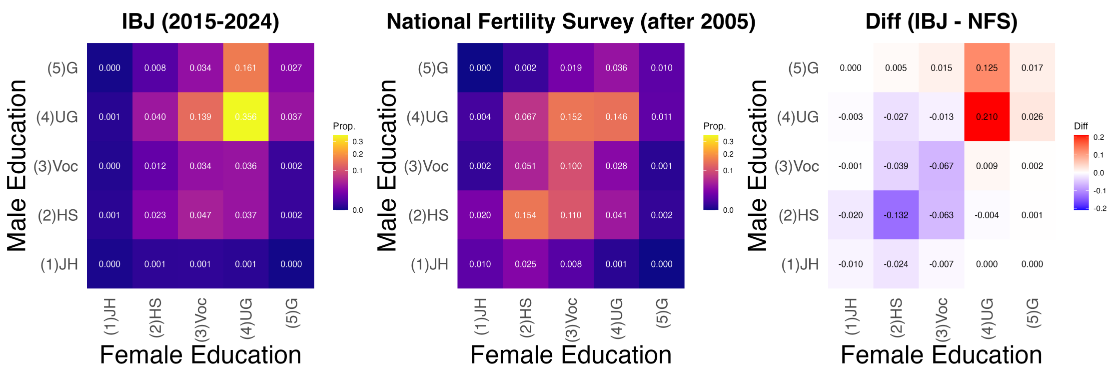
Also, Panel (c) compares the income distribution of IBJ matched couples with that of dual-earner households in the Employment Status Survey (ESS, *Shugyo Kozo Kihon Chosa*), restricting attention to wives under age 55 whose year of marriage is not identified. The income-by-income matrix shows that IBJ couples are more concentrated in higher income categories for both men and women. This pattern is partly mechanical and reflects several factors. First, because IBJ participants are older on average, they are more likely to be observed at higher points of the life-cycle earnings profile. Second, selection into the platform and institutional screening rules—such as minimum income requirements for participation—shift the distribution toward higher income groups. Finally, an important conceptual distinction arises from measurement: the ESS records post-marital household income, whereas IBJ captures individual income prior to matching. In nationally representative post-marriage data, particularly for women, labor supply and earnings may adjust substantially around childbirth and early childrearing, potentially obscuring pre-marital sorting patterns. As a result, income matrices based on post-marital data may conflate assortative matching with subsequent intra-household labor supply responses, whereas IBJ provides a cleaner measure of sorting based on pre-marital income.

At the same time, the comparison highlights an important conceptual distinction. The Employment Status Survey measures household income after marriage at the household unit level, whereas IBJ records individual income prior to matching. In nationally representative post-marriage data, particularly for women, employment status and earnings may change substantially around childbirth and early childrearing, potentially obscuring pre-marital sorting patterns. As a result, income matrices constructed from post-marital household data may conflate sorting with subsequent intra-household labor supply adjustments. Taken together, these comparisons suggest that while IBJ overrepresents higher-income couples relative to the general population, its pre-marital income measures provide a cleaner lens for studying marital sorting than post-marriage household income data.

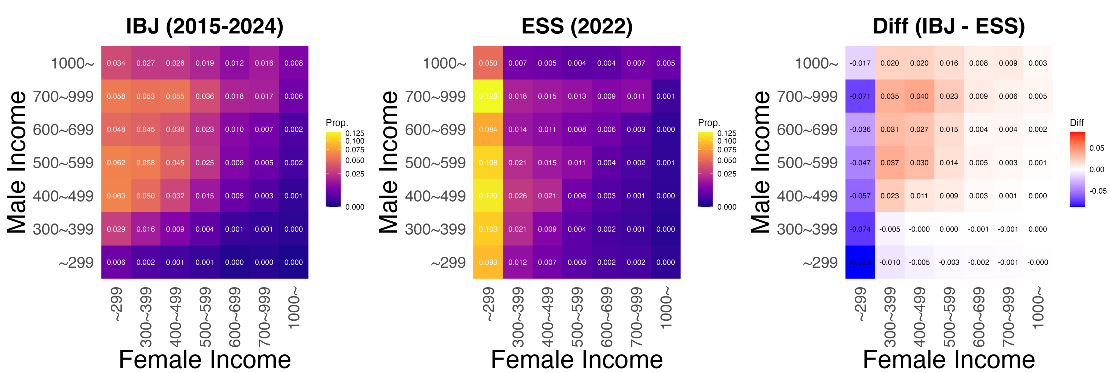
Figure 3 presents the same comparisons using likelihood ratios (LR), which net out marginal-distribution differences and isolate assortative-matching strength. The LR heatmaps show that, after controlling for composition, positive age assortative matching is broadly similar between IBJ and Vital Statistics. The main-diagonal concentration persists in both datasets, indicating comparable age sorting once composition is controlled for. For education, LR comparisons with the National Fertility Survey likewise show positive within-category assortative matching in both samples, though the relative intensity differs across cells: IBJ exhibits comparatively stronger concentration in some lower- and middle-education pairings, whereas the National Fertility Survey shows stronger concentration in the highest education cells. For income, the LR comparison with the Employment Status Survey also indicates positive assortative matching in both datasets. The broad structure is similar, but differences remain at the extremes: the ESS exhibits stronger concentration in the very highest income cell, whereas IBJ shows relatively more concentration in some lower-female-income pairings. These LR comparisons suggest that IBJ-national differences mainly reflect composition shifts toward older and more educated users, while the underlying sorting structure



(a) Age (Proportion)



(b) Education (Proportion)



(c) Income (Proportion)

Figure 2: IBJ Market Coverage Compared with National Statistics (NFS, VS, and ES): Proportion

Note: Panels display the joint proportion $P(i, j) = n_{ij}/N$ for each cell (i, j), where n_{ij} is the number of couples in cell (i, j) and N is the total number of couples. IBJ age data cover 2015–2024 matched with Vital Statistics 2015–2023; education data compare IBJ 2015–2024 with the National Fertility Survey (after 2005); income data compare IBJ 2015–2024 with the Employment Status Survey (2022).

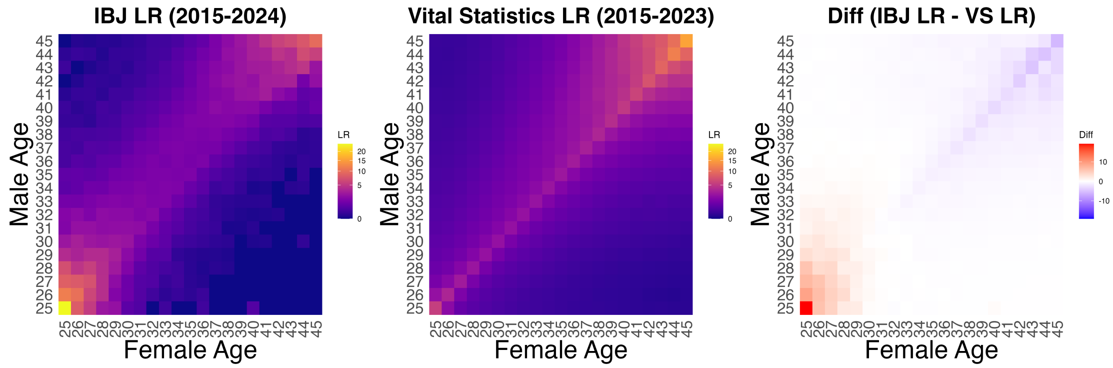
remains broadly comparable.

Taken together, these comparisons show that IBJ is a sizable, policy-relevant segment of the Japanese marriage market, while attracting an older and more educated population than the national average. Once marginal-distribution differences are accounted for, the underlying assortative-matching structure—especially for age and education—is broadly comparable to representative data. We therefore interpret IBJ patterns as reflecting both compositional selection into the platform and genuine matching behavior, and account for both in later analyses.

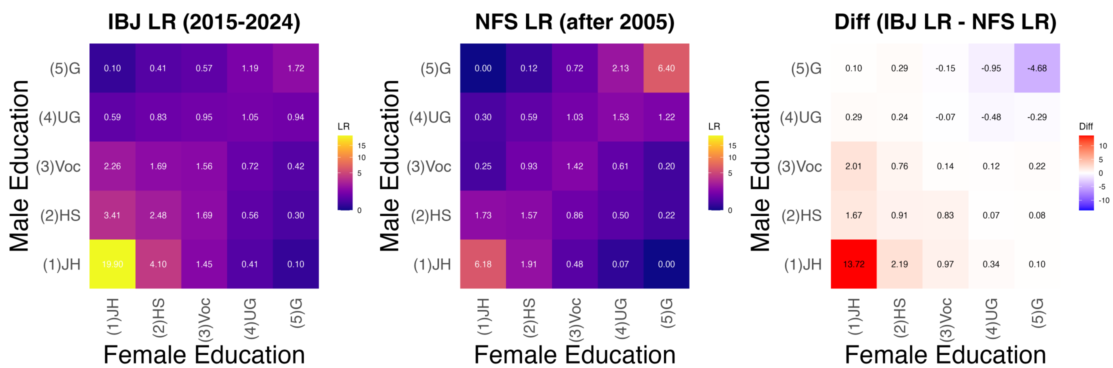
Verified Matches. In this study, a match is a confirmed engagement formed on IBJ through mutual agreement. Because the platform enforces strict rules—including a ban on concurrent engagements and consultant-mediated confirmation—observed engagements are highly credible indicators of successful match formation. Engagements are also time-stamped and linked to full behavioral histories, allowing us to trace when and how matches form (Section 2.2). This design minimizes false positives and makes matching operationally clear and empirically reliable.

Verified Variables IBJ data include highly verified demographic and behavioral variables. Key covariates—age, education, income, health information, and marital history—are cross-checked with government documents, tax records, and certified medical exams. User behavior is tracked at high frequency with timestamps, covering searches, proposals, messages, and mutual agreement. This data integrity contrasts with typical self-reported online-dating (Hitsch *et al.* 2010a) and survey datasets (Dupuy and Galichon 2014, Chiappori *et al.* 2024) and supports rigorous analysis of matching outcomes and behavioral determinants. For the main empirical exercise, we restrict to the balanced sample with non-missing values for all variables used in the affinity matrix.

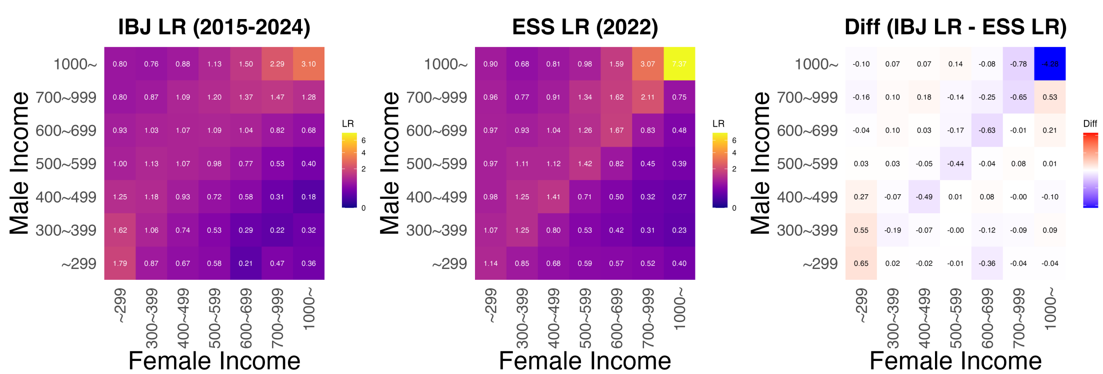
The data also contain occupation categories. Because employer information is observed during income verification, recorded occupations are highly reliable. Following Goldin (2014), we build an occupational-flexibility index by mapping occupations to characteristics that capture how strongly jobs reward long, inflexible hours. Characteristics come from Japan's Occupational Information Network (O-NET), developed by the Ministry of Health, Labour and Welfare and modeled on U.S. O*NET. We use five occupation-level characteristics from Goldin (2014): time pressure, contact with others, interpersonal relationships, structured work, and freedom to make decisions. Each is standardized to mean zero and unit variance at the occupation level and averaged within each IBJ occupation category across corresponding O-NET occupations. The final flexibility index averages the five standardized components, with signs normalized so higher values indicate greater flexibility. Although occupational flexibility is not a standard marriage-market attribute, it captures time-use constraints and career dynamics central to intra-household allocation, so it is plausibly relevant for partner selection.



(a) Age (Likelihood Ratio)



(b) Education (Likelihood Ratio)



(c) Income (Likelihood Ratio)

Figure 3: IBJ Market Coverage Compared with National Statistics (NFS, VS, and ESS): Likelihood Ratio

Note: Panels report the likelihood ratio (LR), defined as $\text{LR}_{ij} = P(i,j)/[P_{\text{male}}(i) \times P_{\text{female}}(j)]$, where $P_{\text{male}}(i) = \sum_j P(i,j)$ and $P_{\text{female}}(j) = \sum_i P(i,j)$ are the marginal distributions because proportions are influenced by marginal distributions (e.g., the overall age or education composition of men and women). $\text{LR}_{ij} = 1$ indicates that the frequency of pairing (i,j) is consistent with random matching; $\text{LR}_{ij} > 1$ indicates over-representation (positive sorting) and $\text{LR}_{ij} < 1$ indicates under-representation relative to what marginal frequencies alone would predict. The LR thus isolates the sorting pattern net of compositional differences between the two populations. IBJ age data cover 2015–2024 matched with Vital Statistics 2015–2023; education data compare IBJ 2015–2024 with the National Fertility Survey (after 2005); income data compare IBJ 2015–2024 with the Employment Status Survey (2022).

2.2 IBJ Users' Dating Process and Stage

Table 1 summarizes IBJ's sequential partner-formation process and the distinction between non-exclusive exploration and exclusive commitment. The process starts at Application, where users browse profiles and can initiate contact by sending an *omiai* request. Initiation is not gender-specific: both men and women can apply. A request advances to Omiai Meeting only if accepted, after which the pair meets in person or online and independently decides whether to continue.

If both parties approve after the first meeting, they enter Pre-relationship, a sequence of non-exclusive dates. At this stage, users may interact with multiple partners and repeatedly decide whether to continue or exit each match. If both then choose to deepen the relationship, they move to the exclusive Serious relationship stage. This stage involves repeated committed dates with the same partner, though either party can still exit. The process ends at Proposal (engagement/matching), which requires mutual confirmation of intent to marry. Overall, the platform moves users gradually from open search to exclusive commitment through mutually agreed steps.

Table 1: Dating Process by Stage, Agent, and Action

Stage	**Agent**	**Action**	**Note**
1. Application	Proposer	Browse candidate profiles	Set filter conditions
	Proposer	Click on candidate profiles	Expressing interest
	Proposer	Send omiai request	Initiates non-exclusive interaction
	Receiver	Accept or reject omiai request	
2. Omiai Meeting	Both	Conduct omiai meeting	Face-to-face or virtual meeting
	Both	Accept or reject trial dating	Decision to continue or exit
3. Pre-relationship	Both	Begin first trial date	Non-exclusive
	Both	Accept or reject second trial date	Decision to continue or exit
	Both	Proceed with additional trial dates	Repeated decision process
	Both	Accept or reject committed dating	Transition to exclusive dating
4. Serious relationship	Both	Begin first date	Exclusive
	Both	Accept or reject second date	Decision to continue
	Both	Proceed with additional dates	Repeated decision process
5. Proposal	Both	Accept marriage engagement	

Table 2 reports stage-specific activity counts per user in 2024, by gender, for users who matched at least once at Application. Because the sample is conditioned on initial Application activity, later-stage counts—Pre-relationship, Serious relationship, and Proposal—can be zero for users who exit earlier. Counts pool proposer and receiver roles and capture total stage-level engagement. The table shows a sharp funnel: Application activity is very intensive and dispersed for both genders (mean counts above 100 with large standard deviations), while participation drops sharply later. Average activity falls to just above two at Pre-relationship, around 0.2 at Serious relationship, and about 0.1 at Proposal, indicating substantial attrition as interactions move toward exclusivity and commitment. This implies that Proposal-stage assortativeness can reflect cumulative selection across stages, not only final-agreement preferences.

Table 2: Summary Statistics of Dating Process Counts Per User in 2024 by Gender: Matched Couples

Gender		N	Mean	SD	Min	Max
Male	Application	56915	119.93	210.58	1.00	15788.00
	Pre-relation	56915	2.28	3.25	0.00	50.00
	Serious-relation	56915	0.21	0.43	0.00	3.00
	Proposal	56915	0.10	0.31	0.00	1.00
Female	Application	60064	113.64	134.29	1.00	2376.00
	Pre-relation	60064	2.16	2.92	0.00	39.00
	Serious-relation	60064	0.20	0.42	0.00	3.00
	Proposal	60064	0.10	0.30	0.00	1.00

Note: The table reports stage-specific counts per user in 2024 for users who matched at least once at the Application stage. As a result, counts at later stages may be zero for users who exited earlier. The statistics pool actions across proposer and receiver roles and summarize total stage-level participation rather than role-specific behavior.

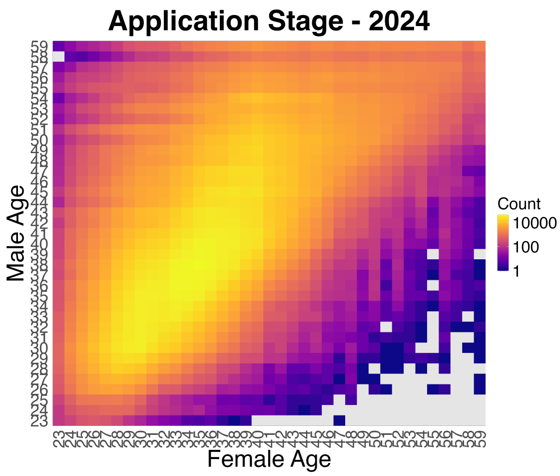
Figure 4 provides a complementary view of age matching across stages in 2024. In this one-dimensional age view, heatmaps show clear diagonal concentration even at Application, suggesting age-assortative interactions from search onset. But because the figure conditions only on age, apparent assortativeness may partly reflect selection on correlated attributes—such as education, income, or family preferences—that users jointly consider when initiating and continuing interactions. One-dimensional age patterns therefore cannot distinguish whether assortative matching originates early or is induced by multidimensional sorting on richer covariates.

These patterns motivate our subsequent analysis, which examines when assortative matching along different dimensions first emerges and how it evolves as matches are selectively retained or discarded throughout the dating process.

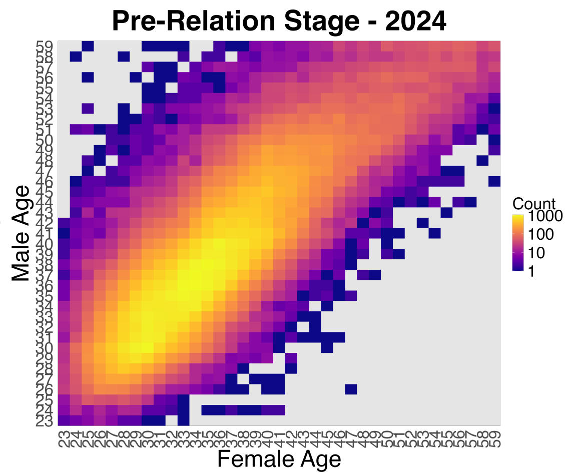
2.3 Summary Statistics of Matched Users in 2024

Table 3 reports the summary statistics of matched couples. In 2024, men in our matched sample are on average approximately 3 years older than women (39.06 vs. 36.01), taller by about 13 cm (171.65 cm vs. 158.67 cm), and heavier by roughly 16 kg (65.19 kg vs. 49.40 kg), resulting in a higher BMI on average. Men also report higher annual income, with a mean upper-limit income category of 782.91 (in 10,000 JPY) compared to 503.62 for women. These differences reflect well-established gender patterns in age, physical attributes, and earning potential in the marriage market. The distributions of these variables are tightly clustered around the means, as indicated by relatively small standard deviations in age (7.15 for women, 8.02 for men) and income (208.45 for women, 347.35 for men, in 10,000 JPY). While the mean flexibility index is identical for men and women at -0.21, the distribution differs markedly across genders: the standard deviation is substantially larger for women (0.49) than for men (0.35), indicating greater dispersion in occupational flexibility among women.

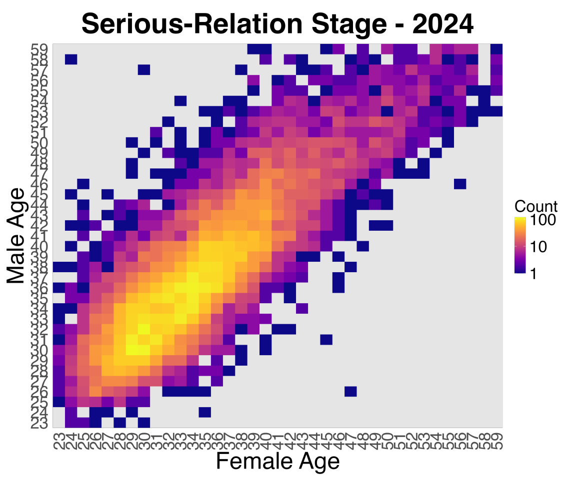
In terms of discrete attributes, educational attainment differs by category across genders.



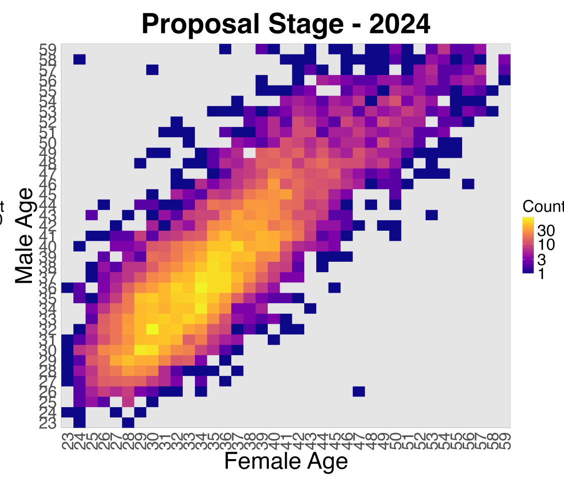
(a) Application



(b) Pre-relationship



(c) Serious relationship



(d) Proposal

Figure 4: Matching Matrix per Stage in 2024: Based on Age

Note: Application stage includes all couples who applied for meetings in 2024. Pre-relationship, Serious relationship, and Proposal stages include couples who progressed to each respective stage in 2024.

Women are more concentrated in vocational and undergraduate categories (22.6% and 62.0%, respectively), whereas men are much more likely to hold graduate degrees (24.2% vs. 6.7% for women). Drinking and smoking habits also differ sharply by gender: 26.2% of men are regular drinkers compared to 15.5% of women, and 3.4% of men regularly smoke versus 0.3% of women. Meanwhile, the majority of both genders report never having been married before (88.4% of women and 84.8% of men). Regarding household preferences, most respondents in both groups favor either discussing housework with a partner or sharing it equally, but women are more likely to report taking primary responsibility themselves (9.1% vs. 4.6%), whereas men are more likely to favor equal sharing (70.3% vs. 56.1%). Childcare preferences are similarly centered on equal sharing, while stated desire for children is high for both genders: 71.5% of women and 70.7% of men report wanting children, with men somewhat more likely to report no clear preference (25.7% vs. 21.8%).

2.4 Preferences and Their Socioeconomic Correlates

Because these preference measures are rarely observed before marriage and are mostly absent from administrative data, it is informative to examine how they co-vary with anthropometric and sociodemographic characteristics used in matching research. Their empirical relationship with age, income, education, and occupation provides a first indication of whether preferences form an independent heterogeneity margin or merely proxy for existing socioeconomic traits. We therefore first describe the distribution of these variables across standard demographic dimensions before presenting structural assortative-matching estimates.

Preference Distribution across Age, Income, Education Panel (a) in Figure 5 shows clear age gradients in fertility preferences for both genders, with a steeper age-related decline in desire for children among women. Younger women and men mostly report wanting children, but at older ages the share of women reporting no desire or no clear preference rises more sharply. Income gradients exist for both genders and appear steeper for men: higher-income men are more likely to want children than lower-income men, while women's fertility preferences vary less across income groups. Along education, the share wanting children generally rises with attainment, consistent with the fertility-education gradient in Doepke *et al.* (2023). The distribution is broadly similar across genders, though lower-educated women appear somewhat more polarized than lower-educated men. Overall, fertility preferences show demographic gradients and gender asymmetries, especially by age.

In Panel (b), "share equally" dominates childcare preferences in almost all demographic groups, but gender asymmetries remain. Women are more likely to report active childcare involvement, while men are somewhat more likely to favor discussion or delegation. Age differences are modest for both genders, though younger cohorts show more dispersion. Income gradients are limited overall, but higher-income men appear slightly more supportive of equal sharing than lower-income men, while women's responses are relatively stable across income levels. By education, higher-educated individuals—especially women—tend to cluster more around equal sharing.

A similar but stronger asymmetry appears in housework preferences in Panel (c). Although

Table 3: Summary Statistics in 2024 by Gender: Matched Couples

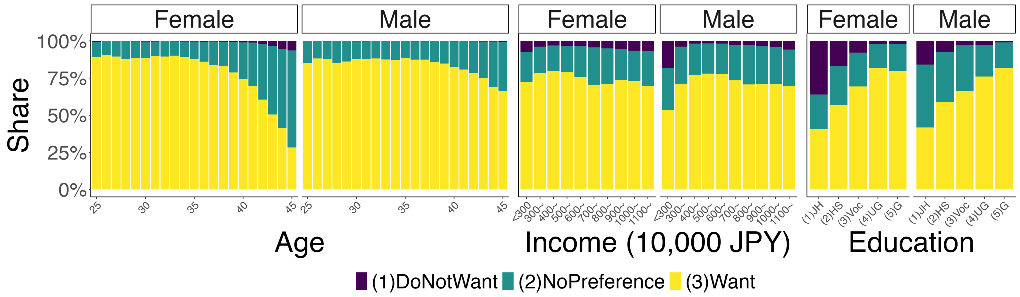
(a) Continuous

Gender		N	mean	median	sd	min	max
female	Age	7562	36.01	35.00	7.15	23.00	75.00
	Income (upper limit)	7511	503.62	500.00	208.45	300.00	2100.00
	Height	7562	158.67	158.00	5.36	142.00	180.00
	Weight	7562	49.40	50.00	7.38	35.00	95.00
	Flexibility	7554	-0.21	-0.24	0.49	-1.45	1.12
male	Age	7561	39.06	38.00	8.02	23.00	79.00
	Income (upper limit)	7544	782.91	700.00	347.35	300.00	2100.00
	Height	7561	171.65	172.00	5.75	152.00	196.00
	Weight	7561	65.19	65.00	9.88	40.00	95.00
	Flexibility	7544	-0.21	-0.24	0.35	-1.45	0.90

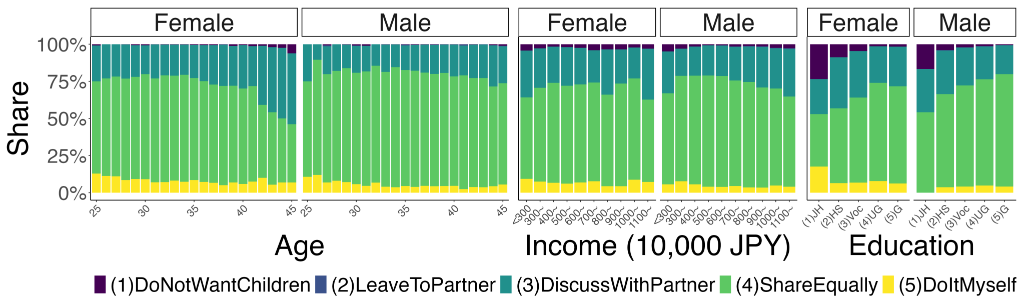
(b) Discrete

		female		male	
		N	Pct.	N	Pct.
Educational level	(1)JuniorHigh	11	0.1	21	0.3
	(2)HighSchool	604	8.0	763	10.1
	(3)Vocational	1709	22.6	619	8.2
	(4)Undergraduate	4698	62.0	4207	55.5
	(5)Graduate	504	6.7	1834	24.2
	NA	51	0.7	133	1.8
Drink Alcohol level	(1)Never	1549	20.4	912	12.0
	(2)SocialOnly	4838	63.9	4661	61.5
	(3)DrinkRegularly	1175	15.5	1988	26.2
	NA	15	0.2	16	0.2
Smoking level	(1)Never	7504	99.0	7092	93.6
	(2)Occasionally	35	0.5	210	2.8
	(3)Regularly	23	0.3	259	3.4
	NA	15	0.2	16	0.2
Marital History Dummy	(1)NeverMarried	6695	88.4	6426	84.8
	(2)DivorcedOrWidowed	867	11.4	1135	15.0
	NA	15	0.2	16	0.2
Housework Share Level	(1)LeaveToPartner	2	0.0	20	0.3
	(2)DiscussWithPartner	2227	29.4	1596	21.1
	(3)ShareEqually	4247	56.1	5326	70.3
	(4)DoItMyself	693	9.1	352	4.6
	NA	408	5.4	283	3.7
Child Care Share Level	(1)DoNotWantChildren	250	3.3	134	1.8
	(2)LeaveToPartner	0	0.0	4	0.1
	(3)DiscussWithPartner	2000	26.4	1702	22.5
	(4)ShareEqually	4297	56.7	5107	67.4
	(5)DoItMyself	505	6.7	306	4.0
	NA	525	6.9	324	4.3
Desired Child Dummy	(1)DoNotWant	493	6.5	256	3.4
	(2)NoPreference	1652	21.8	1950	25.7
	(3)Want	5417	71.5	5355	70.7
	NA	15	0.2	16	0.2

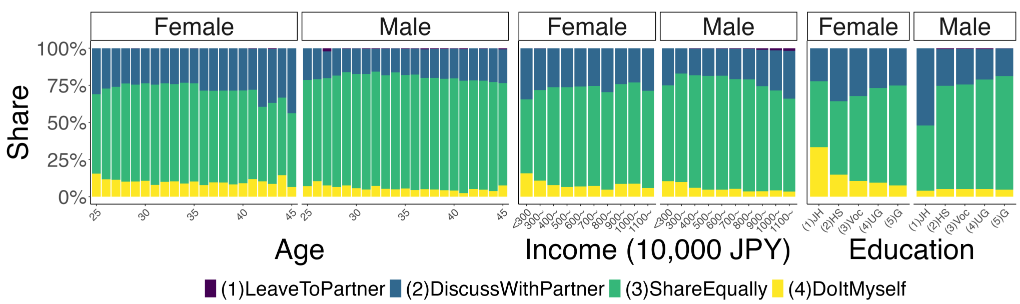
Note: Income represents the upper limit of the income category. Occupational Flexibility follows Goldin (2014).



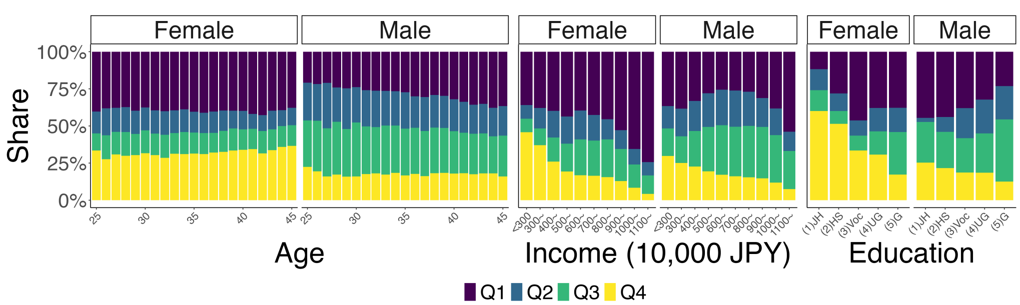
(a) Preference for Children



(b) Childcare



(c) Housework



(d) Occupational Flexibility

Figure 5: Preference Distribution across Age, Income, Education for Matched Users in 2024

"share equally" is still the modal response for both genders, women are less likely than men to choose unilateral non-involvement and more likely to report sharing or taking responsibility themselves. Dispersion across alternatives is larger for men with lower income and education, indicating greater heterogeneity in male housework attitudes in those groups. Age gradients are weak for both genders, but gender gaps persist across demographics. Compared with fertility preferences, housework attitudes show stronger gender asymmetry and somewhat weaker socioeconomic stratification.

In Panel (d), occupational flexibility shows the strongest socioeconomic structuring and clear gender differences in dispersion. Higher-income and higher-education groups are more likely to appear in upper flexibility quartiles for both genders, but women are more dispersed across quartiles within comparable demographic categories. In particular, women appear more represented at both the highest and lowest flexibility levels in some education groups, while men's distribution is more concentrated. Age gradients are less systematic than for fertility preferences, but dispersion asymmetry by gender remains. Unlike household preferences, which show moderate gender differences, occupational flexibility reflects structural differences in labor-market positioning across genders.

Correlation Matrix To assess whether preference measures capture an independent heterogeneity margin or proxy for standard socioeconomic traits, we examine the full correlation structure among attributes for matched users. Table 4 reports pairwise correlations by gender in 2024. This complements the distributional evidence above and shows how strongly fertility and household preferences align statistically with age, education, income, and anthropometric characteristics.

Overall, preference variables are only weakly correlated with most sociodemographic and anthropometric characteristics, suggesting a distinct heterogeneity dimension. For both men and women, child preference is strongly negatively correlated with age, consistent with declining fertility intentions at older ages, but only modestly correlated with education and income. Household-responsibility preferences (housework and childcare) are positively correlated with child preference, especially among women, yet have limited association with education, income, height, or weight. By contrast, standard sociodemographic variables are more tightly interrelated: education and income are positively correlated for both genders, and height and weight are strongly correlated within gender. Gender asymmetries also appear: age is more strongly negatively correlated with fertility preferences among women, and childcare preferences are more internally coherent among women. Taken together, the correlations reinforce that fertility and household preferences form a relatively independent sorting margin rather than simply reflecting socioeconomic gradients.

2.5 Trends in Covariate Distributions of Matched Users, 2015–2024

Figure 6 presents trends in anthropometric and sociodemographic characteristics of individuals in married couples over the 2015–2024 period. Panels (a)–(d) show boxplots of age, height, weight, and BMI by gender, revealing broadly stable distributions and persistent gender gaps across years. In contrast, panels (e) and (f) depict notable shifts in the composition of income and educational attainment. Among women, the income distribution shifts steadily toward higher categories over

Table 4: Correlation Matrix by Gender: Matched Users in 2024

(a) Male

	Educ	Age	Income	Flex	Height	Weight	Drink	Smoke	M Hist	House	C Care	C Pref
Educ	1.000											
Age	-0.185	1.000										
Income	0.145	0.298	1.000									
Flex	-0.028	-0.008	-0.137	1.000								
Height	0.017	-0.032	0.052	-0.011	1.000							
Weight	-0.050	0.081	0.054	-0.017	0.476	1.000						
Drink	0.031	0.027	0.093	0.000	0.036	0.073	1.000					
Smoke	-0.135	0.078	0.014	0.006	0.019	0.063	0.073	1.000				
M Hist	-0.104	0.439	0.231	-0.029	0.025	0.012	0.037	0.066	1.000			
House	0.044	-0.131	-0.132	0.045	-0.003	-0.054	-0.004	-0.059	-0.075	1.000		
C Care	0.101	-0.319	-0.094	0.012	0.021	-0.029	-0.013	-0.067	-0.184	0.567	1.000	
C Pref	0.174	-0.524	-0.057	-0.032	0.040	-0.015	-0.013	-0.065	-0.345	0.070	0.357	1.000

(b) Female

	Educ	Age	Income	Flex	Height	Weight	Drink	Smoke	M Hist	House	C Care	C Pref
Educ	1.000											
Age	-0.239	1.000										
Income	0.271	0.071	1.000									
Flex	-0.095	0.093	-0.214	1.000								
Height	0.038	0.018	0.067	-0.006	1.000							
Weight	-0.064	0.049	-0.002	0.006	0.422	1.000						
Drink	0.052	-0.005	0.127	-0.032	0.053	0.062	1.000					
Smoke	-0.082	0.059	-0.020	0.014	-0.001	0.024	0.027	1.000				
M Hist	-0.165	0.424	-0.014	0.058	-0.007	-0.039	-0.012	0.053	1.000			
House	0.024	-0.109	-0.013	0.029	-0.003	-0.011	-0.007	-0.027	-0.059	1.000		
C Care	0.134	-0.395	0.014	-0.043	-0.008	-0.012	0.025	-0.041	-0.246	0.457	1.000	
C Pref	0.212	-0.606	0.013	-0.100	0.008	-0.023	0.014	-0.066	-0.397	0.095	0.470	1.000

Note: Income represents the upper limit of the income category. Occupational Flexibility follows Goldin (2014).

time, with declining shares in the lower bins and rising shares in the 5-million-JPY-and-above categories. This upward shift suggests that women's economic attractiveness—traditionally less emphasized in the marriage market—has become increasingly important. Educational attainment also moves modestly upward, particularly among women, with a gradual rise in the undergraduate share and a corresponding decline in vocational categories.

Figure 7 illustrates the evolution of lifestyle habits, marital history, and family preferences among married individuals from 2015 to 2024. Panels (a) and (b) show that smoking is rare while drinking is dominated by social drinking, and gender gaps persist: women are consistently less likely to drink regularly or smoke, though the share of regular female drinkers increased modestly over time. Panel (c) reveals a stable yet notable gender difference in marital history, with remarriage being more common among men than women. Panel (d) shows that the desire to have children remains widespread, but the share expressing no preference has grown gradually for both genders, indicating a slight softening of parenthood norms. Panels (e) and (f), which become informative only in the most recent years and are effectively observed from 2023 onward, highlight significant gender asymmetries in stated preferences for the division of childcare and housework. Men are somewhat more likely to prefer discussion or delegation, whereas women more frequently endorse shared or self-led responsibilities. These gender gaps in family role preferences have remained sizable and persistent since their introduction in the survey, with only limited signs of convergence.

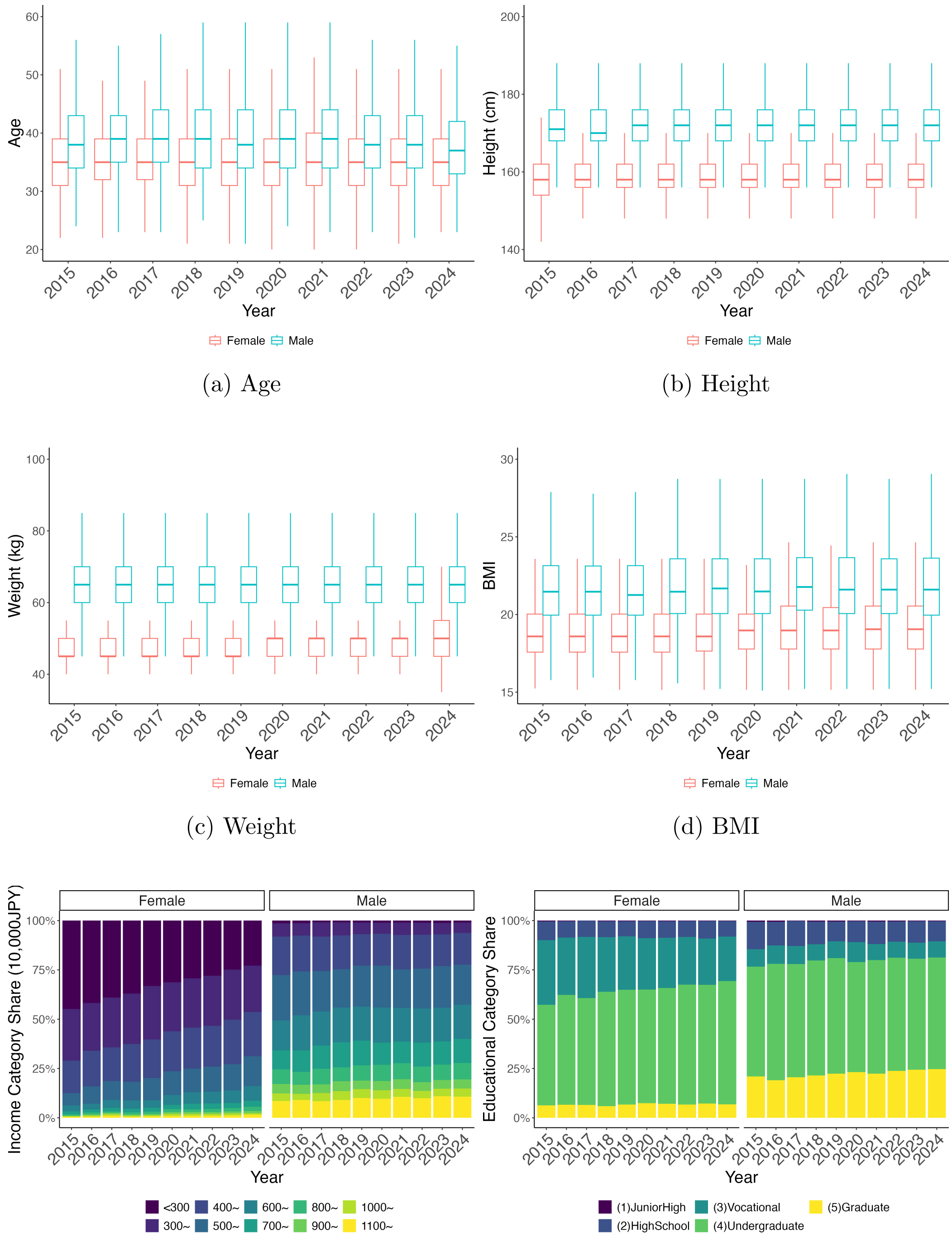
Figure 8 shows that the median occupational flexibility index is very similar for men and women throughout the period. In contrast, the distribution is consistently more dispersed among women, with a wider interquartile range and longer tails, indicating greater heterogeneity in occupational flexibility. There is no clear time trend in the distribution for either gender over the sample period.

3 Model

This section outlines empirical multidimensional matching frameworks with transferable utility that are used to document sorting patterns in the marriage market. Subsection 3.1 reviews the flexible and tractable multidimensional one-to-one matching model of Dupuy and Galichon (2014), which is well suited to describing final matching patterns in the Proposal stage. Subsection 3.2 discusses the matching-with-trading-networks framework of Fox (2018). Although this model requires an additional normalization and cross-market assumptions, which limit coefficient-level interpretability, it accommodates many-to-many matching and is therefore appropriate for dating stages where agents can interact with multiple potential partners.

3.1 TU Multidimensional Continuous-Type Quadratic Matching Model

We consider a frictionless transferable-utility marriage market in which each man and woman is described by observable characteristics, denoted $x \in \mathcal{X}$ for men and $y \in \mathcal{Y}$ for women. The matching outcome is governed by a probability measure $\pi(x, y)$ giving the likelihood that type-x men and type-y women match. Upon matching, partners receive deterministic utility components



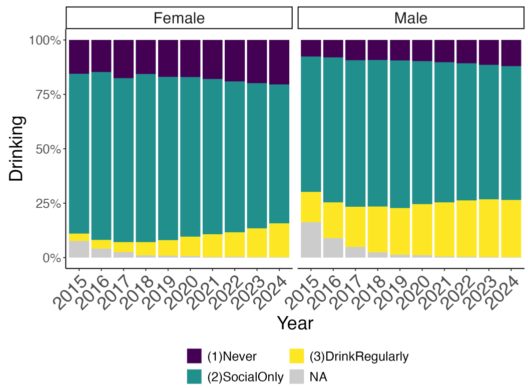
(a) Age (b) Height

(c) Weight (d) BMI

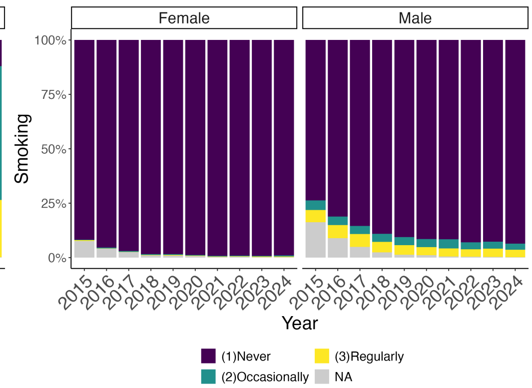
(e) Income Category (f) Education

Figure 6: Distribution and Share of Anthropometric and Sociodemographic Attractiveness in Married Couples

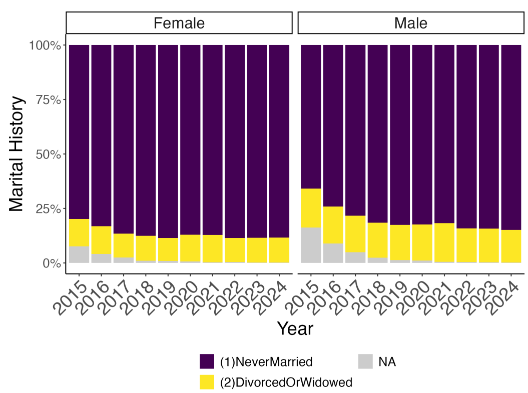
Note: In each boxplot, the central box represents the interquartile range (IQR), spanning from the 25th to the 75th percentile of the distribution, with the horizontal line inside indicating the median (50th percentile). The vertical lines ("whiskers") extend to the most extreme values within 1.5 times the IQR from the box; values beyond this range are considered outliers and are not shown in the plot.



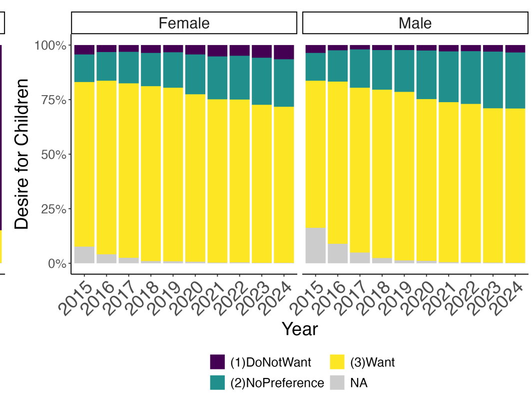
(a) Drinking



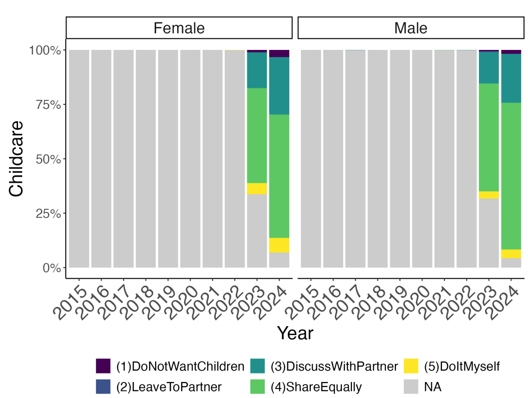
(b) Smoking



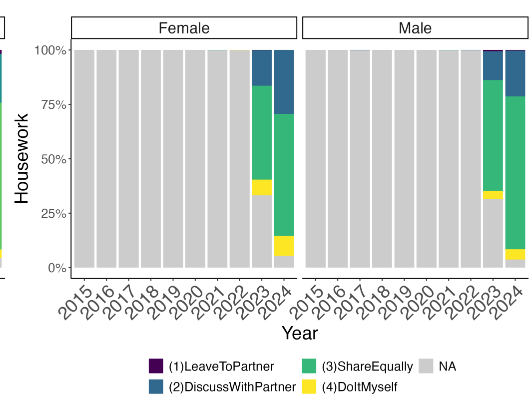
(c) Marital History



(d) Preference for Children



(e) Childcare



(f) Housework

Figure 7: Share of Lifestyle, Marital History, and Family Preferences in Married Couples

Note: See Chiappori *et al.* (2018b) and Chiappori *et al.* (2024) for discussion of the use of smoking variables.

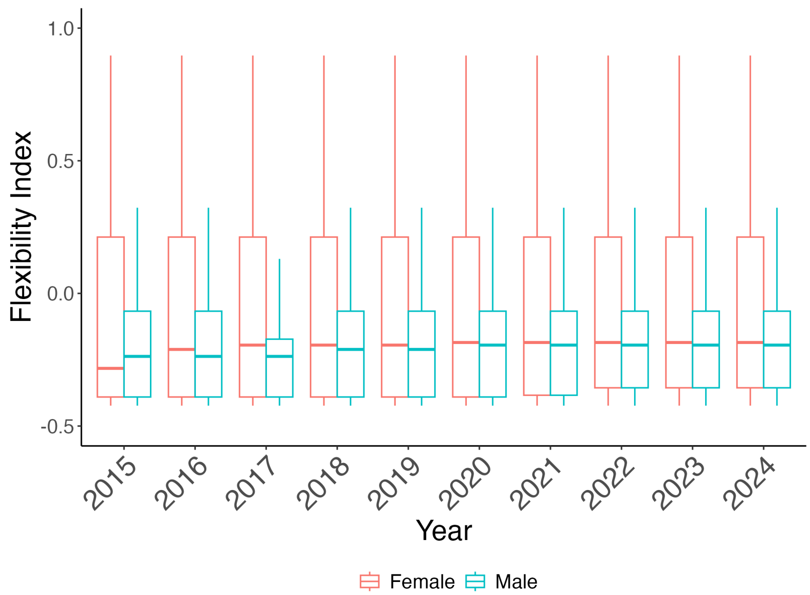


Figure 8: Distribution of Occupational Flexibility in Married Couples

Note: In each boxplot, the central box represents the interquartile range (IQR), spanning from the 25th to the 75th percentile of the distribution, with the horizontal line inside indicating the median (50th percentile). The vertical lines ("whiskers") extend to the most extreme values within 1.5 times the IQR from the box; values beyond this range are considered outliers and are not shown in the plot.

$U(x, y)$ and $V(x, y)$ plus individual-specific stochastic shocks.

Following Dupuy and Galichon (2014), each agent draws an infinite sequence of potential partners characterized by observables and idiosyncratic preference shocks. For men, matches are evaluated over $\{(y^k, \varepsilon^k)\}_{k=1}^{\infty}$, where each ε^k is i.i.d. type I extreme value. This yields a continuous-logit formulation in which utility from matching with y^k is $U(x, y^k) + \frac{\sigma}{2}\varepsilon^k$, with σ governing the relative importance of idiosyncratic versus systematic preferences. The same formulation applies for women.

Under this assumption, the equilibrium matching probabilities and surplus shares satisfy the following structure. The joint matching density $\pi(x, y)$ is characterized by

$$\pi(x, y) = \exp\left(\frac{\Phi(x, y) - a(x) - b(y)}{\sigma}\right),$$

where $\Phi(x, y)$ is total systematic surplus and $a(x)$, $b(y)$ are type-specific adjustment terms ensuring that matches do not exceed type supplies. Surplus shares are then:

$$U(x, y) = \frac{\Phi(x, y) + a(x) - b(y)}{2},$$
$$V(x, y) = \frac{\Phi(x, y) + b(y) - a(x)}{2}.$$

Parameterization and estimation. To make the model empirically implementable, we rely on a quadratic specification of the systematic surplus function, following Dupuy and Galichon (2014):

$$\Phi(x, y) = x'Ay = \sum_{i,j \in \{1,\cdots,O\}} x_i A_{ij} y_j.$$

The $O \times O$ affinity matrix A summarizes how traits interact in matching and is the central object of interest. Its elements encode both magnitude and sign: positive a_{ij} indicates complementarity between traits x_i and y_j, while negative values indicate substitutability.

Estimation exploits the equilibrium structure. As shown by Dupuy and Galichon (2014), $B = A/\sigma$ is recovered as the solution to

$$\min_B \left\{ \mathcal{W}(B, 1) - E_{\hat{\pi}} \left[x'By \right] \right\}$$

where $\mathcal{W}(A, \sigma)$ denotes the social gain maximized at the equilibrium matching π (Shapley and Shubik 1971):

$$\mathcal{W}(A, \sigma) \equiv \max_{\pi \in \mathcal{M}} \left\{ E_\pi[x'Ay] - \sigma E_\pi[\log\, \pi(x, y)] \right\},$$

where expectations indexed by $\hat{\pi}$ are computed from the empirical joint distribution of observed matches.

Optimality conditions yield moment-matching restrictions. Intuitively, the estimated model must reproduce the joint characteristic distribution observed in matches. In particular, the implied equilibrium matching distribution equates predicted and empirical cross-moments of male and female traits:

$$E_\pi[X_i Y_j] = E_{\hat{\pi}}[X_i Y_j]$$

for every pair of characteristics (i, j). In practice, estimation selects B so model-implied assortative patterns align with the empirical ones.

Saliency analysis. An important implication of the quadratic specification is that it admits a low-dimensional representation of assortative forces. In particular, A can be factorized by singular value decomposition (SVD), which transparently characterizes both the number and nature of economically relevant sorting dimensions. Formally, A can be written as

$$A = U' \Lambda V$$

where Λ is a diagonal matrix of positive singular values (largest to smallest), and U and V contain the associated loading vectors. Each singular value captures the relative importance of a sorting dimension, while loadings describe how observables map to that dimension on each market side.

This decomposition rewrites surplus as a sum of independent components. Defining $\tilde{x} = Ux$

and $\tilde{y} = Vy$, surplus is

$$\Phi(x, y) = x'Ay = \sum_{k=1}^{K} \lambda_k \tilde{x}_k \tilde{y}_k$$

where each term captures the contribution of one assortative dimension. In this representation, sorting operates through orthogonal indices, with larger singular values indicating more salient dimensions.

In the empirical analysis, we apply this decomposition to $\hat{A}$ to recover U, V, and Λ. This allows us to assess both relative salience across sorting dimensions and the trait combinations defining each dimension. Sampling uncertainty is quantified by bootstrap procedures.

A remaining issue is dimensionality. Following Dupuy and Galichon (2014), we conduct rank-based tests on the estimated affinity matrix. The null imposes $rank(A) = k$; rejection implies sorting along more than k economically relevant dimensions.

Identification with multiple years. Because the data span 2015–2024, one can estimate yearly affinity matrices and study changes in sorting forces. However, A is identified only up to scale (only $B = A/\sigma$ is identified), so additional restrictions are needed for cross-year comparisons.

To enable such comparisons, we follow Ciscato and Weber (2020) and normalize each year's affinity matrix to unit Frobenius norm, $\|A^t\| = 1$. [11] Under this normalization, we have $\frac{B^t}{\|B^t\|} = A^t$ and $\sigma^t = \frac{1}{\|B^t\|}$. After estimating B^t, we recover A^t, which is directly comparable across years and allows analysis of time trends in sorting. The time series of σ^t then tracks changes in the relative importance of unobserved heterogeneity.

3.2 A Many-to-Many TU Matching Model for Multi-Stage Partner Formation

This subsection adapts the transferable-utility (TU) matching-with-trading-networks framework of Fox (2018) to IBJ's multi-stage partner-formation pipeline (Section 2.2) and defines stage-specific assortativeness measures using continuous attributes.[12] The goal is to identify at which stage of the matching process assortative patterns along different dimensions first emerge, rather than to compare the magnitude of assortativeness across stages.

At each stage, agents can form multiple relationships, and equilibrium outcomes are characterized as competitive allocations over trade portfolios (Azevedo and Hatfield 2018), not single matches. Preferences depend on observables, with deterministic surplus parameterized linearly by stage-specific coefficients. Restricting to bilinear interactions between male and female continuous attributes yields a stage-specific affinity matrix: diagonal elements capture assortative matching, off-diagonals capture cross-attribute complementarities. Identification uses the rank-order property under exchangeable unobserved heterogeneity, and estimation uses matching maximum score,

[11] Ciscato *et al.* (2020) propose an alternative normalization in which $\mathcal{W}(A, \sigma) = 1$. Note that the optimal matching function $\pi(x, y)$ depends only on $B = A/\sigma$, and is therefore invariant to the choice of normalization.

[12] Our use of "trade" follows Fox (2018): a trade is a relationship instance encoding observable characteristics of both participants and, optionally, additional observable contract/stage features. See Fox (2018) for trading-network equilibrium and matching maximum score estimation.

delivering set-consistent stage-specific affinity estimates up to scale.

3.3 Technical Distinction Between Dupuy and Galichon (2014) and Fox (2018)

Although both this framework and Dupuy and Galichon (2014) use bilinear surplus specifications, they differ fundamentally in equilibrium concept and identifying variation. Dupuy–Galichon is a one-to-one continuous-logit model where entropic regularization yields a unique matching density and point identification of the scaled affinity matrix $B = A/\sigma$ (or, equivalently, a normalized version of A), rather than the unrestricted level of A. By contrast, Fox (2018) is nonparametric in unobserved heterogeneity and identifies preferences only up to scale via equilibrium stability inequalities. Hence, affinity matrices here are not comparable across stages or over time in levels; interpretation is based on sign robustness and within-stage relative importance. Accordingly, Dupuy–Galichon is used for cross-sectional levels and long-run Proposal-stage trends, while Fox is used to identify when assortative patterns become robust along the pipeline.

4 Estimation Results

This section presents the empirical results in three steps. We first characterize the structure of assortative matching at the Proposal stage using the multidimensional affinity matrix estimated following Dupuy and Galichon (2014). We then document how the strength of assortative matching along key dimensions has evolved over the past decade at the Proposal stage, as in Ciscato and Weber (2020). Finally, we use a many-to-many framework in the spirit of Fox (2018) to examine when assortative patterns begin to emerge along the matching pipeline.

4.1 Affinity Matrix at the Proposal Stage in 2024

We begin by examining the cross-sectional structure of preferences at the Proposal stage in the most recent year. Table 5 reports the estimated affinity matrix for 2024 based on the multidimensional matching framework of Dupuy and Galichon (2014). It yields three notable insights into sorting patterns and preference structures in the marriage market.

Sociodemographic and Anthropometric Attributes. The affinity matrix reveals positive assortative matching along sociodemographic and anthropometric attributes. Diagonal elements for age, education, income, height, and weight are all positive, indicating that individuals tend to match with partners who are similar along these dimensions. Because all attributes are measured prior to matching, these patterns reflect sorting behavior rather than post-marital coordination.

Among these attributes, age exhibits the largest diagonal coefficient (3.55), substantially exceeding those of other characteristics. Other sociodemographic and anthropometric variables also display positive assortative matching, with diagonal coefficients ranging between 0.17 and 0.21.

Cross-attribute interactions among sociodemographic and anthropometric traits are present and, in some cases, asymmetric. For example, the interaction between education and age is negative, indicating that, conditional on own age, higher education is associated with matching to younger partners. The interaction between education and income is positive, implying that more educated individuals tend to match with higher-income partners conditional on their own income. This interaction exhibits modest asymmetry: the coefficient for male education–female income (0.11) exceeds that for male income–female education (0.07). Interactions involving physical attributes also display asymmetry. The interaction between male height and female age is negative (–0.23), whereas the corresponding interaction between female height and male age is small (–0.03) and statistically indistinguishable from zero. This pattern indicates that the contribution of sociodemographic and anthropometric attributes to match surplus differs by gender, consistent with gender-specific roles, expectations, or signaling in the marriage market.

Occupational Flexibility. Occupational flexibility, constructed following Goldin (2014), exhibits positive assortative matching, although the magnitude of the diagonal coefficient is small (0.03). Relative to sociodemographic and anthropometric attributes, occupational flexibility plays a more limited role in the affinity matrix.

Ex-ante theoretical predictions regarding assortative matching in occupational flexibility are ambiguous. If flexibility facilitates within-household specialization, it may function as a substitutable characteristic across spouses, reducing incentives for positive sorting. By contrast, positive assortative matching may arise if spouses' inputs to home production are complementary, a mechanism supported by recent evidence showing that such complementarities have strengthened over time (Calvo *et al.* 2024). In a related vein, recent work by Almar *et al.* (2025a) documents positive assortative matching along educational ambition, measured using expected initial wage levels and wage growth. Because educational ambition is negatively associated with hours flexibility, their findings suggest assortative matching in occupational characteristics related to flexibility.[13]

Interactions involving occupational flexibility are also limited. In particular, nearly all interaction coefficients between flexibility and other attributes are statistically indistinguishable from zero, with standard errors ranging between 0.01 and 0.03. As a result, occupational flexibility contributes relatively little to overall sorting patterns at the Proposal stage.

Household Preferences. Household-related preferences play a quantitatively important role in sorting at the Proposal stage. In particular, the diagonal coefficient on desire for children is large (0.25), making it the second-largest diagonal element in the affinity matrix after age. This magnitude exceeds that of education, income, and all other anthropometric and preference-related attributes, indicating that alignment in fertility preferences is a major source of match surplus. Diagonal coefficients for childcare and housework preferences are also positive, though smaller in magnitude, confirming assortative matching along multiple dimensions of household orientation.

[13] Assortative matching may also reflect preferences for partners in similar occupational environments. While empirical studies have reported occupational similarities between spouses (e.g., Kalmijn 1994), some recent work finds that preferences for similar occupations play a limited role in partner selection (Belot and Francesconi 2013, Lee 2016, Mansour and McKinnish 2018).

These results suggest that early alignment in household expectations plays an important role in match formation, even before such preferences are behaviorally realized in marriage.

Interactions among household preferences further clarify the structure of this alignment. For example, interactions between childcare preferences and desire for children are positive (0.05 and 0.06 across gender pairs), whereas interactions between housework preferences and desire for children are negative (-0.06 and -0.04). These patterns indicate that household preferences interact in a structured way: individuals with strong fertility preferences tend to match with partners willing to assume childcare responsibilities, while preferences over housework exhibit a more differentiated relationship with fertility preferences. More generally, these coefficients show that alignment across household-related attributes does not necessarily imply similarity, but rather reflects systematic complementarities and trade-offs in household roles that contribute to match surplus.

By contrast, interactions between preferences for children and most sociodemographic or anthropometric attributes are small, with age as a notable exception. In particular, the interaction between male child preference and female age is negative, while interactions with education, income, height, and weight are otherwise limited. This implies that fertility preferences constitute a distinct margin of sorting that operates largely independently of education, income, and most physical characteristics. Taken together, these patterns show that preferences for children are not only strongly assortative but also form a separate dimension of matching, rather than serving as proxies for traditional sociodemographic attributes.

Factor Decomposition. We further assess whether the estimated sorting patterns can be summarized by a low-dimensional structure using the saliency decomposition of Dupuy and Galichon (2014). Table 6 reports the relative importance and factor loadings of the leading indices implied by the estimated affinity matrix. The hypothesis that a single index fully captures sorting patterns is rejected. Nevertheless, three indices together account for nearly 90% of the observable matching surplus, indicating that sorting operates along a small number of economically meaningful dimensions.

The first index is the dominant source of variation, accounting for more than 70% of total saliency for both men and women. This index loads almost exclusively on age, with loading coefficients of –0.97 for men and –0.99 for women. The magnitude and isolation of these loadings indicate that age-based sorting remains the most salient dimension of marriage formation. The strong and isolated weight on age suggests that partners tend to form matches within narrowly defined birth cohorts (e.g., Chiappori *et al.* 2024).

The second index explains approximately 9% of total saliency and captures variation in sociodemographic and anthropometric attributes. It loads positively on education (0.26 for men, 0.20 for women), income (0.65 and 0.40), and height (0.49 and 0.47), while loading negatively on weight (–0.43 and –0.71), with notable gender differences in magnitudes. Income (0.65) and height (0.49) are most salient for men, while weight (-0.71) and height (0.47) play a more prominent role for women. This index therefore reflects sorting along a bundle of characteristics associated with sociodemographic status and physical attractiveness, beyond pure age similarity.

The third index is primarily driven by preferences for children for both men (-0.89) and women (-0.91). Although it accounts for only 6% of total saliency, this dimension represents a distinct margin of sorting that is not subsumed by sociodemographic or anthropometric characteristics. Moreover, because individuals search for partners only within their cohort, the contribution of this index to joint surplus is amplified when conditioning on age, amounting to more than 20% of the remaining surplus. This finding underscores that preferences for children constitute an economically important and independent dimension of assortative matching, despite their comparatively smaller weight in the unconditional decomposition.

Table 5: Estimated Affinity Matrix

	Education	Age	Income	Flexibility	Height	Weight	Drink	Smoke	Marital History	Housework	Childcare	Child
Education	**0.17**	**−0.10**	**0.11**	0.01	0.03	**−0.05**	0.02	−0.02	**−0.03**	0.02	0.00	0.00
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Age	**−0.08**	**3.55**	**−0.21**	0.03	−0.03	**0.11**	**−0.06**	**0.08**	**0.08**	0.03	**−0.08**	−0.03
	(0.03)	(0.07)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income	**0.07**	**−0.74**	**0.20**	−0.01	**0.12**	**−0.27**	**0.04**	−0.01	**0.06**	−0.01	0.03	0.02
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Flexibility	0.01	**0.10**	0.00	**0.03**	0.01	0.00	0.01	−0.01	−0.01	−0.01	−0.00	0.00
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Height	0.03	**−0.23**	**0.08**	0.01	**0.21**	**−0.13**	0.01	**−0.03**	0.02	−0.00	−0.01	**0.06**
	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Weight	−0.03	**0.24**	**−0.06**	−0.00	**−0.07**	**0.20**	0.01	0.02	**−0.04**	−0.00	0.03	−0.03
	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Drink	0.02	−0.03	0.03	0.02	0.01	−0.03	**0.10**	−0.01	0.01	−0.00	0.02	0.01
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Smoke	**−0.03**	**0.12**	−0.02	0.01	0.01	−0.02	0.01	**0.03**	**0.03**	−0.01	0.03	−0.00
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Marital History	**−0.06**	**0.11**	0.02	−0.02	0.02	**−0.04**	**0.04**	**0.02**	**0.12**	0.02	−0.02	**−0.04**
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Housework	0.01	−0.03	0.03	0.00	0.01	−0.01	−0.01	−0.02	0.03	0.02	0.00	**−0.06**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Childcare	0.00	−0.05	−0.01	0.01	−0.02	0.03	0.01	−0.00	−0.00	−0.03	0.02	**0.05**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Child	−0.01	**−0.29**	−0.01	−0.01	0.02	−0.02	**−0.04**	−0.01	−0.01	**−0.04**	**0.06**	**0.25**
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)

Note: We use 6,592 couples to estimate the affinity matrix. All variables are standardized to have unit variance. Income represents the upper limit of the income category. Standard errors, reported in parentheses, are obtained from 2,000 bootstrap replications. Estimates in bold are statistically significant at the 5% level.

Table 6: Saliency Analysis

	Index 1	Index 2	Index 3	Index 4	Index 1	Index 2	Index 3	Index 4
Education	**0.03**	**0.26**	**0.10**	**0.79**	**0.03**	**0.20**	**0.09**	**0.78**
	(0.00)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)
Age	**−0.97**	**0.21**	**−0.08**	0.01	**−0.99**	**0.08**	−0.01	**0.04**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Income	**0.21**	**0.65**	**0.08**	**−0.07**	**0.07**	**0.40**	**0.17**	**0.26**
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)	(0.04)
Flexibility	**−0.03**	0.03	−0.02	**0.13**	−0.01	0.02	−0.01	**0.13**
	(0.01)	(0.02)	(0.04)	(0.04)	(0.01)	(0.03)	(0.04)	(0.04)
Height	**0.07**	**0.49**	**−0.19**	**−0.06**	**0.02**	**0.47**	**−0.12**	**−0.08**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)
Weight	**−0.07**	**−0.43**	0.03	**0.14**	**−0.05**	**−0.71**	−0.01	**0.19**
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
Drink	**0.01**	**0.11**	0.03	**0.09**	**0.02**	**0.08**	**0.17**	−0.01
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)
Smoke	**−0.03**	0.04	−0.01	**−0.21**	**−0.02**	−0.04	0.04	**−0.14**
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.02)	(0.04)	(0.04)
Marital History	**−0.03**	**0.14**	**0.24**	**−0.53**	**−0.02**	**0.20**	**0.14**	**−0.49**
	(0.01)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.03)
Housework	0.01	**0.06**	**0.22**	0.01	−0.01	0.03	**0.19**	0.04
	(0.01)	(0.02)	(0.04)	(0.04)	(0.01)	(0.03)	(0.04)	(0.05)
Childcare	**0.01**	**−0.08**	**−0.20**	0.05	**0.02**	−0.03	**−0.19**	0.04
	(0.01)	(0.03)	(0.04)	(0.05)	(0.01)	(0.03)	(0.04)	(0.04)
Child	**0.08**	0.02	**−0.89**	−0.05	**0.02**	**0.10**	**−0.91**	0.05
	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.03)
Index share	**0.72**	**0.09**	**0.06**	**0.04**	**0.72**	**0.09**	**0.06**	**0.04**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)

Note: The table presents the singular vectors associated with men and women, denoted by U and V, respectively, along with the singular values contained in diag(Λ), obtained from the singular value decomposition of the affinity matrix $A = U'\Lambda V$. The final row reports the elements of diag(Λ), which measure the relative contribution of each underlying sorting dimension. We use 6,592 couples for the saliency analysis. All variables are standardized to have unit variance. Standard errors, reported in parentheses, are obtained from 2,000 bootstrap replications. Estimates in bold are statistically significant at the 5% level.

4.2 Assortative Matching Estimates Under Unidimensional and Multidimensional Specifications

Another important question in the multidimensional matching literature is whether conclusions drawn from parsimonious specifications—often focusing on a single attribute such as education or age—are sensitive to the exclusion of other relevant characteristics. Many empirical studies estimate assortative matching using a limited set of variables, implicitly assuming that omitted attributes neither interact strongly with included ones nor materially affect measured assortativeness. Table 7 examines this issue by progressively enriching the attribute space within the Dupuy–Galichon framework and comparing diagonal coefficients across specifications.

The results indicate that estimates based on parsimonious specifications can differ by economically large magnitudes from those obtained in the fully multidimensional model. When education alone is included, as in Chiappori *et al.* (2017) and Eika *et al.* (2019), the estimated diagonal coefficient is 0.25, compared with 0.17 in the full specification, implying an estimate about 47% larger.[14] This pattern suggests that part of the assortativeness commonly attributed to education reflects its correlation and interaction with other characteristics. A different pattern arises for age. When age alone is used, as in Choo and Siow (2006), the estimated diagonal coefficient is 2.98, compared with 3.55 in the full specification, so the unidimensional estimate is about 16% smaller than the multidimensional benchmark.

By contrast, the specification that includes both age and income produces coefficients much closer to those in the fully specified model: the age coefficient is 3.61 versus 3.55 in the full model, and the income coefficient is 0.22 versus 0.20. This finding suggests that, when the objective is to measure assortativeness along the age and income dimensions, including both variables jointly yields estimates that are broadly consistent with those from the multidimensional benchmark.

At the same time, incorporating additional attributes such as occupational flexibility and household preferences does not materially alter the education–age–income coefficients, indicating that these core sociodemographic dimensions remain relatively stable as the model is further enriched. Nevertheless, several of the added traits—most notably height and preferences for children—exhibit sizable own-trait assortativeness in the fully specified model, in some cases exceeding that of income. These results underscore that preference-based and anthropometric characteristics represent quantitatively distinct and important margins in their own right, with direct implications for the fertility discussion in Section 5.

4.3 Transition of Affinity Matrices at the Proposal Stage: 2015–2024

Having established the structure of assortative matching at the Proposal stage in 2024, we next examine how the strength of assortative matching along each dimension has evolved over time. To enable comparisons across years, we apply the normalization procedure proposed by Ciscato and Weber (2020) explained in Section 3.1. [15]

Table 8 reports the rescaled diagonal elements of the affinity matrix at the Proposal stage from

[14] Unidimensional models do not typically adopt quadratic specifications as in Dupuy and Galichon (2014); therefore, the magnitude reported here does not necessarily imply that existing estimates in the literature overstate assortativeness by 47%. For an extensive exercise, Appendix B.2 estimates unidimensional models for each characteristic as in Choo and Siow (2006).

[15] The method proposed by Dupuy and Galichon (2014) is robust to changes in the marginal distributions and therefore identifies the underlying structure of the surplus function. Accordingly, provided that appropriate normalization is imposed on the parameters, as in Ciscato *et al.* (2020) and Ciscato and Weber (2020), it is possible to analyze variation in affinity matrices over time. Building on this approach, Ciscato *et al.* (2020) compare sorting patterns across different-sex and same-sex marriage markets, while Ciscato and Weber (2020) examine temporal changes in the affinity matrix.

Table 7: Sensitivity to Attribute Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Education	0.25			0.22	0.22		0.18	0.17	0.17
	(0.01)			(0.01)	(0.01)		(0.01)	(0.01)	(0.01)
Age		2.98		2.98		3.61	3.58	3.58	3.55
		(0.06)		(0.06)		(0.07)	(0.07)	(0.07)	(0.07)
Income			0.17		0.16	0.22	0.20	0.19	0.20
			(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Flexibility								0.03	0.03
								(0.01)	(0.01)
Height								0.21	0.21
								(0.02)	(0.02)
Weight								0.20	0.20
								(0.02)	(0.02)
Drink								0.10	0.10
								(0.01)	(0.01)
Smoke								0.03	0.03
								(0.01)	(0.01)
Marital History								0.13	0.12
								(0.01)	(0.01)
Housework									0.02
									(0.02)
Childcare									0.02
									(0.02)
Child									0.25
									(0.02)

Note: The table displays the diagonal elements of the marital preference parameter matrix A, capturing own-trait assortative matching, estimated under progressively richer specifications. Column (1) includes only education; column (2) includes only age; column (3) includes only income; column (4) includes education and age; column (5) includes education and income; column (6) includes age and income; column (7) includes education, age, and income; column (8) further includes flexibility, height, weight, drinking, smoking, and marital history; column (9) presents the full specification with all twelve attributes. Income represents the upper limit of the income category. We use 6,592 couples for these analyses. Standard errors are in parentheses.

2015 to 2024, allowing for a direct comparison of assortative matching patterns over time.[16] Focusing on the endpoints of the sample period, assortative matching by education declines substantially, decreasing from 0.09 in 2015 to 0.05 in 2024 (a decline of 44.4%), indicating a gradual weakening of educational sorting at the final matching stage. In contrast, assortativeness by age remains high throughout the period and increases slightly over the decade, rising from 0.93 to 0.95. This pattern suggests a persistent, and marginally strengthened, role of age similarity in partner selection. Assortative matching by marital history also declines markedly, falling from 0.09 in 2015 to 0.03 in 2024 (a decline of 66.7%). While marital history is the second most salient dimension of assortative matching in 2015, it plays a much more limited role by 2024. By contrast, assortativeness with respect to income, height, weight, and preferences for children remains largely stable between 2015 and 2024 and continues to play an important role in sorting after age. Overall, these patterns point to a modest reallocation of assortative matching at the Proposal stage away from education and marital history toward age, while most other dimensions exhibit stable sorting patterns over the past decade.

Table 8: Transition of Diagonal Elements of Affinity Matrices

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Education	0.09	0.11	0.07	0.08	0.07	0.07	0.06	0.06	0.05	0.05
Age	0.93	0.92	0.92	0.93	0.93	0.94	0.95	0.95	0.95	0.95
Income	0.04	0.05	0.04	0.04	0.05	0.06	0.05	0.04	0.04	0.05
Flexibility	0.01	0.00	0.01	0.02	0.01	0.02	0.00	0.01	0.01	0.01
Height	0.05	0.07	0.08	0.07	0.06	0.06	0.05	0.05	0.06	0.06
Weight	0.06	0.05	0.05	0.05	0.06	0.07	0.05	0.05	0.05	0.05
Drink	0.01	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.03
Smoke	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Marital History	0.09	0.07	0.07	0.05	0.06	0.05	0.04	0.05	0.04	0.03
Child	0.07	0.07	0.07	0.07	0.06	0.07	0.08	0.07	0.07	0.07

Note: The table displays the estimated trend of the diagonal elements of the marital preference parameter matrix A capturing the interaction between husband's and wife's characteristics, rescaled following Ciscato and Weber (2020) to make estimates comparable across years. Income represents the upper limit of the income category.

Table 9: Transition of the Contribution of Unobserved Heterogeneity in Affinity Matrices

	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Sigma	0.27	0.32	0.34	0.32	0.33	0.3	0.27	0.26	0.25	0.27

Note: The table displays the estimated trend of the unobserved heterogeneity σ, following Ciscato and Weber (2020) to make estimates comparable across years.

[16]The contribution of unobserved heterogeneity increases during the early years of the sample period but returns to its initial level by 2024; see Table 9.

4.4 When Does Assortative Matching Emerge? Evidence from Dating Process Data

While the preceding analysis documents both the cross-sectional structure and the long-run evolution of assortative matching at the Proposal stage, it remains unclear at which point in the matching process these patterns begin to form. We therefore utilize our dating process data and turn to a many-to-many matching framework following Fox (2018) to trace the emergence of assortative matching across stages of relationship formation.

Table 10 reports assortative matching estimates from the many-to-many matching framework, with education assortativeness normalized to one within each stage. Given the scale normalization inherent in the maximum score estimator, coefficient magnitudes are interpreted only relative to other covariates within the same stage. Under this interpretation, a limited subset of variables exhibits robust assortative patterns with confidence intervals that exclude zero. Across all stages, assortativeness with respect to age is robustly positive and large relative to education, indicating that age consistently ranks as one of the most salient dimensions of sorting within each stage. Income assortativeness is also robustly positive across stages and smaller than age but clearly larger than education. Family-related characteristics play an important role: assortativeness in marital history and in the presence of children is robustly positive at later stages, indicating that these dimensions are systematically associated with sorting when compared to education within the same stage. By contrast, flexibility, physical attributes, lifestyle variables, housework, and childcare have confidence intervals that include zero in all stages and therefore do not display robust assortative signs under the many-to-many specification.

Because parameters are normalized separately by stage, comparisons of coefficient magnitudes across stages are not meaningful. Instead, the multi-stage estimates are informative about when assortative matching along a given dimension first becomes robustly identified along the matching pipeline. Under this criterion, assortative matching with respect to age and income is already robust at the Application stage and remains robust throughout subsequent stages. In contrast, assortativeness with respect to marital history is not robustly identified at early stages but emerges at later stages of relationship formation, remaining robust through the Proposal stage. These patterns indicate that while some dimensions shape sorting from the outset of search, others become relevant only after earlier screening has occurred. Overall, the many-to-many estimates suggest that assortative matching at the Proposal stage reflects selective continuation along a small set of dimensions whose relevance becomes apparent at different points in the matching process, rather than a monotonic strengthening of sorting intensity across stages.

5 Discussion: Implications for Household Economics

A distinctive feature of our data is that they record individuals' preferences for children at the time of marriage. In Section 4, we document that individuals sort into marriages along these pre-marital preferences. In this section, we discuss the implications of this finding for standard modeling

Table 10: Matching Maximum Score Estimation in 2024

	Application		Pre-Relation		Serious-Relation		Proposal	
Variable	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Education	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]	1.00	[1.00, 1.00]
Age	9.24	[7.64, 9.97]	9.36	[7.86, 9.99]	9.31	[7.92, 9.97]	9.27	[8.24, 9.99]
Income	4.24	[1.38, 7.46]	4.54	[1.12, 8.49]	4.08	[0.33, 7.74]	4.42	[1.79, 7.46]
Flexibility	-0.24	[-2.22, 1.85]	1.04	[-0.72, 3.02]	0.41	[-1.10, 2.46]	-0.34	[-1.99, 1.04]
Height	1.56	[-0.03, 3.93]	1.14	[-0.82, 2.97]	0.69	[-1.06, 2.52]	1.12	[-0.70, 2.79]
Weight	1.60	[-0.72, 4.00]	0.94	[-0.56, 2.73]	1.02	[-0.15, 3.40]	1.68	[-0.08, 3.53]
Drink	0.35	[-1.49, 2.11]	1.12	[-0.54, 3.67]	0.61	[-0.91, 3.01]	1.25	[-0.61, 3.89]
Smoke	0.83	[-8.88, 9.75]	-0.62	[-8.03, 9.07]	3.24	[-5.10, 9.50]	3.45	[-4.35, 9.14]
Marital History	3.79	[-1.15, 9.01]	4.57	[0.49, 8.52]	5.46	[1.92, 9.59]	5.24	[0.93, 9.53]
Housework	0.06	[-1.72, 1.90]	-0.26	[-2.12, 1.51]	0.71	[-1.78, 3.51]	-0.65	[-3.60, 1.59]
Childcare	0.89	[-1.98, 2.90]	1.00	[-1.85, 3.64]	-0.23	[-3.95, 2.96]	0.86	[-2.50, 4.83]
Child	3.48	[-0.74, 8.90]	4.86	[1.17, 9.05]	4.01	[0.80, 9.13]	4.86	[0.53, 9.50]

Note: The objective function was numerically maximized using the differential evolution (DE) algorithm in the `BlackBoxOptim.jl` package. For the DE algorithm, we require setting the domain of parameters and the number of population seeds so that we fix the former to [-10, 10]. For estimation, 100 runs of 1000 seeds were performed for all specifications. The numbers in parentheses are the lower and upper bounds of the set of maximizers of the maximum rank estimator. Parameters that can take on only a finite number of values (here 1) converge at an arbitrarily fast rate, so they are superconsistent. All variables are normalized by subtracting their sample means and dividing by their sample standard deviations. Income represents the upper limit of the income category. The full interaction model is shown in Appendix B.1.

assumptions in household economics, with a particular focus on the interpretation of policy effects in models of fertility and female labor supply.

To illustrate the role of preference-based sorting, we consider a simple static model of fertility and women's labor supply, closely following Section 5.1 of Doepke *et al.* (2023). A unitary household chooses consumption c and the number of children n. Each child entails a monetary cost ψ and a time cost ϕ. A fraction $s \in (0,1)$ of total childcare time is provided through free childcare, which serves as the policy parameter of interest. The man is assumed to work full time at wage w_m, while the woman supplies any remaining childcare after public provision and allocates her remaining time to market work at wage w_f. The household problem is

$$\max_{c,n} \log(c) + \delta \log(n) \qquad s.t. \qquad c + \psi n = w_m + w_f \left[1 - (1-s)\phi n\right] \tag{1}$$

where $\delta \geq 0$ captures the strength of preferences for children. [17] The optimal fertility choice is

$$n = \frac{\delta}{1+\delta} \frac{w_m + w_f}{\psi + (1-s) w_f \phi} \tag{2}$$

[17] We assume a unitary household in which spouses derive identical utility from children, implying that utility is perfectly transferable. This assumption guarantees consistency between the household problem specified in this section and the transferable utility (TU) structure imposed in the estimation following Dupuy and Galichon (2014). An alternative approach would allow for imperfectly transferable utility at the estimation stage and for heterogeneous fertility preferences within the household, as in Doepke and Kindermann (2019), thereby relaxing the TU assumption. We leave this extension for future research.

and female labor supply l_f is given by

$$l_f = 1 - (1-s)n\phi = 1 - \frac{\delta}{1+\delta}\frac{(w_m + w_f)(1-s)\phi}{\psi + (1-s)w_f\phi}. \tag{3}$$

Under the assumption that all households share the same preference parameter δ, fertility and female labor supply are both increasing in the provision of childcare s:

$$\frac{\partial n}{\partial s} = \frac{\delta}{1+\delta}\frac{(w_m + w_f)w_f\phi}{(\psi + (1-s)w_f\phi)^2} > 0 \tag{4}$$

$$\frac{\partial l_f}{\partial s} = \frac{\delta}{1+\delta}\frac{(w_m + w_f)\psi\phi}{(\psi + (1-s)w_f\phi)^2} > 0 \tag{5}$$

Equations 4 and 5 characterize the policy response to childcare expansion in an economy without preference heterogeneity.

Our empirical findings from the multidimensional matching models suggest, however, that couples differ systematically in their preferences for children due to sorting, even conditional on observables such as education. To capture this heterogeneity, suppose instead that there are two types of couples, $t \in \{L, H\}$, with different preferences for children $\delta_L < \delta_H$. Let $p_H \in (0, 1)$ denote the fraction of type H couples, and let $\delta = (1-p_H)\delta_L + p_H\delta_H$ be the economy-wide average preference for children across heterogeneous couples. In this setting, the effects of childcare expansion become

$$\begin{aligned}\frac{\partial n}{\partial s} &= \left((1-p_H)\frac{\delta_L}{1+\delta_L} + p_H\frac{\delta_H}{1+\delta_H}\right)\frac{(w_m + w_f)w_f\phi}{(\psi + (1-s)w_f\phi)^2} \\ &< \frac{\delta}{1+\delta}\frac{(w_m + w_f)w_f\phi}{(\psi + (1-s)w_f\phi)^2},\end{aligned} \tag{6}$$

$$\begin{aligned}\frac{\partial l_f}{\partial s} &= \left((1-p_H)\frac{\delta_L}{1+\delta_L} + p_H\frac{\delta_H}{1+\delta_H}\right)\frac{(w_m + w_f)\psi\phi}{(\psi + (1-s)w_f\phi)^2} \\ &< \frac{\delta}{1+\delta}\frac{(w_m + w_f)\psi\phi}{(\psi + (1-s)w_f\phi)^2}.\end{aligned} \tag{7}$$

As a result, models that abstract from sorting on preferences for children overstate the average policy response of fertility and female labor supply to childcare expansion. [18]

The economic intuition can be illustrated by an extreme case in which preferences for children

[18] The same logic extends to other parameters. For example, the marginal effects of an increase in female wages are given by

$$\frac{\partial n}{\partial w_f} = \frac{\delta}{1+\delta}\frac{\psi - (1-s)w_m\phi}{[\psi + (1-s)w_f\phi]^2}, \tag{8}$$

$$\frac{\partial l_f}{\partial w_f} = -\frac{\delta}{1+\delta}\frac{(1-s)\phi\,[\psi - (1-s)w_m\phi]}{[\psi + (1-s)w_f\phi]^2}. \tag{9}$$

Allowing for heterogeneity in preferences for children similarly attenuates these responses in magnitude. An analogous argument applies to changes in the monetary cost of children, ψ, which is closely related to analyses of child subsidy policies.

are highly polarized across couples. At one end, some couples derive no utility from having children (i.e., $\delta_L = 0$) and therefore choose not to have children regardless of policy interventions that lower childcare costs or subsidize fertility. For these couples, policies such as expanded childcare provision generate no behavioral response. At the other end, couples with strong preferences for children do respond to such policies. However, these couples are also more likely to already have children, so additional policy-induced reductions in the cost of childrearing translate into relatively small increases in fertility due to diminishing marginal utility from additional children. Because utility from children is concave, a feature supported empirically (e.g., Wang 2025), the positive responses among high-preference couples cannot compensate for the absence of responses among low-preference couples. As a result, models that abstract from heterogeneity and sorting in fertility preferences tend to overstate the aggregate policy response.

Although the preceding argument relies on a highly stylized static framework, the assumption of homogeneous preferences for children [19] is common in empirical analyses of fertility and female labor supply, in part because of identification challenges (e.g., Bick 2016, Garcia-Moran and Kuehn 2017, Yamaguchi 2019, Kim *et al.* 2024, Jakobsen *et al.* 2024). [20] In this context, our results suggest that policy simulations conducted under homogeneous-preference assumptions may overstate the effects of childcare provision and related family policies. While sorting on preferences for children is not, in itself, unexpected, documenting its role at the marriage stage highlights the importance of accounting for both preference heterogeneity and matching when evaluating policy counterfactuals.[21]

6 Conclusion

This paper shows that pre-marital preferences—especially preferences for children—are a first-order determinant of marriage market sorting. While much of the existing literature emphasizes sorting on education, income, or other observable characteristics, far less is known about sorting on the preferences that directly govern household behavior, largely because such preferences are rarely observed prior to marriage and are often measured only after household decisions have already been made.

We address this gap using unique data from a structured marriage matching platform in Japan that record a rich set of attributes and preferences prior to matching and verify them using official documents. By focusing on pre-marital information, we isolate sorting patterns that are not confounded by post-marital coordination or household specialization. A multidimensional matching framework reveals pervasive assortative matching across attributes, but also highlights a clear

[19] Preferences for children are sometimes allowed to vary by education, but are typically assumed to be homogeneous at the individual or couple level conditional on observables. Even when preference heterogeneity by education is permitted, the same logic applies: policy effects estimated separately by education group may be misleading if there is sorting on preferences conditional on education.

[20] Some studies depart from this assumption by incorporating heterogeneity in preferences for children (e.g., Adda *et al.* 2017, Wang 2025).

[21] Almar and Ishihata (2026) jointly model marriage and fertility decisions with heterogeneity in fertility preferences to allow for sorting on these dimensions.

distinction between sociodemographic and anthropometric characteristics—whose interactions are widespread—and preferences, which constitute a separate margin of sorting. In particular, preferences for children emerge as one of the most salient dimensions, second only to age and exceeding education in importance. Exploiting the platform's staged matching process in a many-to-many framework, we further show that sorting on age and income is already present at the initial Application stage, whereas sorting on preferences—most notably preferences for children—emerges only at later stages through selective continuation.

These findings have important implications for empirical and theoretical work on household behavior. Models that link marriage market sorting to fertility, labor supply, or intra-household allocation often abstract from heterogeneity in underlying preferences, implicitly assuming that households with similar observables face similar trade-offs. Our theoretical exercise illustrates that this abstraction can be misleading: when individuals sort on preferences prior to marriage, ignoring such heterogeneity leads to biased predictions of policy effects on household decisions such as labor supply and fertility.

More broadly, our results suggest that observed sorting on standard characteristics may mask deeper sorting on primitives that are typically unobserved in conventional data. Incorporating clean measures of pre-marital preferences into matching models offers a promising avenue for improving the empirical foundations of household economics. An important direction for future research is to link pre-marital preference sorting to post-marital outcomes—such as fertility, labor supply, and child investments—in order to better understand how household formation shapes long-run inequality and the effectiveness of family policies.

References

Abdellaoui, A., Borcan, O., Chiappori, P.-A., Hugh-Jones, D., Torvik, F. A. and Ystrøm, E. (2023). Trading social status for genetics in marriage markets: evidence from great britain and norway.

Adda, J., Dustmann, C. and Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, **125** (2), 293–337.

—, Pinotti, P. and Tura, G. (2025). There's more to marriage than love: the effect of legal status and cultural distance on intermarriages and separations. *Journal of Political Economy*, **133** (4), 1276–1333.

Ahn, S. Y. (2025). Matching across markets: An economic analysis of cross-border marriage. *Journal of Labor Economics*, **43** (2), 000–000.

Almar, F., Friedrich, B., Reynoso, A., Schulz, B. and Vejlin, R. M. (2025a). *Educational ambition, marital sorting, and inequality*. Tech. rep., National Bureau of Economic Research.

—, —, —, — and — (2025b). *Families' Career Investments and Firms' Promotion Decisions*. Tech. rep., National Bureau of Economic Research.

— and Ishihata, Y. (2026). *Fertility, marriage market equilibrium, and education choice*. Tech. rep., Working paper.

— and Schulz, B. (2024). Optimal weights for marital sorting measures. *Economics Letters*, **234**, 111497.

Azevedo, E. M. and Hatfield, J. W. (2018). Existence of equilibrium in large matching markets with complementarities. *Available at SSRN 3268884*.

Bang, M. (2021). Job flexibility and household labor supply: Understanding gender gaps and the child wage penalty.

Bapna, R., Ramaprasad, J., Shmueli, G. and Umyarov, A. (2016). One-way mirrors in online dating: A randomized field experiment. *Management Science*, **62** (11), 3100–3122.

Belot, M. and Francesconi, M. (2013). Dating preferences and meeting opportunities in mate choice decisions. *Journal of Human Resources*, **48** (2), 474–508.

Bick, A. (2016). The quantitative role of child care for female labor force participation and fertility. *Journal of the European Economic Association*, **14** (3), 639–668.

Buyukeren, B., Makarin, A. and Xiong, H. (forthcoming). The impact of dating apps on young adults: Evidence from tinder. *American Economic Journal: Applied Economics*.

Calvo, P. (2025). *The Effects of Institutional Gaps between Cohabitation and Marriage*. Tech. rep., Working paper.

—, Lindenlaub, I. and Reynoso, A. (2024). Marriage market and labour market sorting. *Review of Economic Studies*, **91** (6), 3316–3361.

Chiappori, P.-A., Ciscato, E. and Guerriero, C. (2024). Analyzing matching patterns in marriage: Theory and application to italian data. *Quantitative Economics*, **15** (3), 737–781.

—, Costa-Dias, M., Crossman, S. and Meghir, C. (2020a). Changes in assortative matching and inequality in income: Evidence for the uk. *Fiscal Studies*, **41** (1), 39–63.

—, Dias, M. C. and Meghir, C. (2018a). The marriage market, labor supply, and education choice. *Journal of Political Economy*, **126** (S1), S26–S72.

—, —, — and Zhang, H. (2025). Changes in marital sorting: Theory and evidence from the united states. *Journal of Political Economy*, **133** (10), 3045–3077.

—, Fiorio, C. V., Galichon, A. and Verzillo, S. (forthcoming). Assortative matching on income. *Econometrica*.

— and Low, C. (2024). Frictionless one-to-one matching with transfers: Theory. In *Handbook of the Economics of Matching*, vol. 1, Elsevier, pp. 1–39.

—, Oreffice, S. and Quintana-Domeque, C. (2012). Fatter attraction: anthropometric and socioeconomic matching on the marriage market. *Journal of Political Economy*, **120** (4), 659–695.

—, — and — (2016). Black–white marital matching: race, anthropometrics, and socioeconomics. *Journal of Demographic Economics*, **82** (4), 399–421.

—, — and — (2018b). Bidimensional matching with heterogeneous preferences: education and smoking in the marriage market. *Journal of the European Economic Association*, **16** (1), 161–198.

—, — and — (2020b). Erratum: Fatter attraction: Anthropometric and socioeconomic matching on the marriage market. *Journal of Political Economy*, **128** (12), 4673–4675.

— and Salanié, B. (2023). Mating markets. In *Handbook of the Economics of the Family*, vol. 1, Elsevier, pp. 49–109.

—, Salanié, B. and Weiss, Y. (2017). Partner choice, investment in children, and the marital college premium. *American Economic Review*, **107** (8), 2109–2167.

Choo, E. and Siow, A. (2006). Who marries whom and why. *Journal of political Economy*, **114** (1), 175–201.

Ciscato, E. (2024). Assessing racial and educational segmentation in large marriage markets. *Review of Economic Studies*, p. rdae115.

—, Galichon, A. and Goussé, M. (2020). Like attract like? a structural comparison of homogamy across same-sex and different-sex households. *Journal of Political Economy*, **128** (2), 740–781.

— and Goussé, M. (2024). *Matching on gender and sexual orientation*. Tech. rep., IZA Discussion Papers.

— and Weber, S. (2020). The role of evolving marital preferences in growing income inequality. *Journal of Population Economics*, **33** (1), 307–347.

Cortés, P. and Pan, J. (2019). When time binds: Substitutes for household production, returns to working long hours, and the skilled gender wage gap. *Journal of Labor Economics*, **37** (2), 351–398.

Doepke, M., Hannusch, A., Kindermann, F. and Tertilt, M. (2023). The economics of fertility: A new era. In *Handbook of the Economics of the Family*, vol. 1, Elsevier, pp. 151–254.

— and Kindermann, F. (2019). Bargaining over babies: Theory, evidence, and policy implications. *American Economic Review*, **109** (9), 3264–3306.

Dupuy, A. and Galichon, A. (2014). Personality traits and the marriage market. *Journal of Political Economy*, **122** (6), 1271–1319.

Egebark, J., Ekström, M., Plug, E. and Van Praag, M. (2021). Brains or beauty? causal evidence on the returns to education and attractiveness in the online dating market. *Journal of Public Economics*, **196**, 104372.

Eika, L., Mogstad, M. and Zafar, B. (2019). Educational assortative mating and household income inequality. *Journal of Political Economy*, **127** (6), 2795–2835.

Erosa, A., Fuster, L., Kambourov, G. and Rogerson, R. (2022). Hours, occupations, and gender differences in labor market outcomes. *American Economic Journal: Macroeconomics*, **14** (3), 543–590.

Fisman, R., Iyengar, S. S., Kamenica, E. and Simonson, I. (2006). Gender differences in mate selection: Evidence from a speed dating experiment. *The Quarterly Journal of Economics*, **121** (2), 673–697.

Fox, J. T. (2018). Estimating matching games with transfers. *Quantitative Economics*, **9** (1), 1–38.

Frémeaux, N., Jung, S. and Lefranc, A. (2024). Assortative mating and earnings inequality in south korea. *The Journal of Economic Inequality*, **22** (1), 211–236.

Galichon, A. and Salanié, B. (2022). Cupid's invisible hand: Social surplus and identification in matching models. *The Review of Economic Studies*, **89** (5), 2600–2629.

Garcia-Moran, E. and Kuehn, Z. (2017). With strings attached: Grandparent-provided child care and female labor market outcomes. *Review of Economic Dynamics*, **23**, 80–98.

Gayle, G.-L. and Shephard, A. (2019). Optimal taxation, marriage, home production, and family labor supply. *Econometrica*, **87** (1), 291–326.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American economic review*, **104** (4), 1091–1119.

Greenwood, J., Guner, N., Kocharkov, G. and Santos, C. (2014). Marry your like: Assortative mating and income inequality. *American Economic Review*, **104** (5), 348–353.

Hitsch, G. J., Hortaçsu, A. and Ariely, D. (2010a). Matching and sorting in online dating. *American Economic Review*, **100** (1), 130–163.

—, — and Ariely, D. (2010b). What makes you click?—mate preferences in online dating. *Quantitative marketing and Economics*, **8** (4), 393–427.

Hoehn-Velasco, L. and Penglase, J. (2023). Changes in assortative matching and educational inequality: evidence from marriage and birth records in mexico. *Journal of Demographic Economics*, **89** (4), 587–607.

Jakobsen, K. M., Jørgensen, T. H. and Low, H. (2024). Fertility and family labor supply.

Kalmijn, M. (1994). Assortative Mating by Cultural and Economic Occupational Status. *American Journal of Sociology*, **100** (2), 422–452.

Kim, S., Tertilt, M. and Yum, M. (2024). Status externalities in education and low birth rates in korea. *American Economic Review*, **114** (6), 1576–1611.

Lee, S. (2016). Effect of online dating on assortative mating: Evidence from south korea. *Journal of Applied Econometrics*, **31** (6), 1120–1139.

Lindenlaub, I. (2017). Sorting multidimensional types: Theory and application. *The Review of Economic Studies*, **84** (2), 718–789.

— and Postel-Vinay, F. (2023). Multidimensional sorting under random search. *Journal of political Economy*, **131** (12), 3497–3539.

Low, C. (2024). The human capital–reproductive capital trade-off in marriage market matching. *Journal of Political Economy*, **132** (2), 552–576.

Manski, C. F. (1975). Maximum score estimation of the stochastic utility model of choice. *Journal of econometrics*, **3** (3), 205–228.

Mansour, H. and McKinnish, T. (2018). Same-occupation spouses: preferences or search costs? *Journal of Population Economics*, **31** (4), 1005–1033.

Ong, D. and Wang, J. (2015). Income attraction: An online dating field experiment. *Journal of Economic Behavior & Organization*, **111**, 13–22.

Otani, S. (2025). Nonparametric estimation of matching efficiency and elasticity in a marriage agency platform: 2014–2025. *Economics Letters*, **256**, 112617.

Reynoso, A. (2024). The impact of divorce laws on the equilibrium in the marriage market. *Journal of Political Economy*, **132** (12), 4155–4204.

Salanié, B. (2024). Matching with transfers: Applications. In *Handbook of the Economics of Matching*, vol. 1, Elsevier, pp. 40–78.

Shapley, L. S. and Shubik, M. (1971). The assignment game i: The core. *International Journal of game theory*, **1** (1), 111–130.

Shiue, C. H. and Keller, W. (2022). *Marriage Matching over Five Centuries in China*. Tech. rep., National Bureau of Economic Research.

Wang, H. (2025). Fertility and family leave policies in germany: Optimal policy design in a dynamic framework. *Working paper*.

Yamaguchi, S. (2019). Effects of parental leave policies on female career and fertility choices. *Quantitative Economics*, **10** (3), 1195–1232.

Zheng, Q., van Alten, S., Lyngstad, T. H., Ciscato, E., Sun, Z., Miao, J., Wu, Y., Dorn, S., Zheng, B., Havdahl, A. *et al.* (2025). Genetic basis of partner choice. *bioRxiv*, pp. 2025–02.

A Appendix: Data

A.1 IBJ Data Advantage Compared with Related Literature

Table 11 summarizes recent literature. Relative to the existing marriage-matching literature, our IBJ platform data uniquely combine (i) a rich set of verified pre-marital attributes and stated preferences, (ii) observation of both matched and unmatched users, and (iii) high-frequency, stage-by-stage logs that track the full matching pipeline from initial applications to Proposal—features that are rarely available simultaneously in administrative registries, surveys, or census-based studies.

Table 11: Comparison of Recent Marriage Matching Studies

Data and Observation Design				
Paper	**Data Source**	**Match Observation**	**Unmatched Observed**	**Timing Resolution**
Chiappori *et al.* (forthcoming)	Dutch Admin. tax	Couples (marriage year)	No	Annual
Chiappori *et al.* (2024)	Italian parent survey	Couples (rich traits)	No	Post-marriage
Abdellaoui *et al.* (2023)	GB/NO Biobank	Couples (genetic, SES)	Partial	Cross-sectional
Almar and Schulz (2024)	Danish registers	Couples (edu programs)	Yes	Panel
Hoehn-Velasco and Penglase (2023)	MX marriage registry	New marriages	No	Annual
Shiue and Keller (2022)	CN genealogies	Historical matches	No	Inferred
Chiappori *et al.* (2025)	US Census (IPUMS)	Education bins	No	Cohort
Chiappori *et al.* (2020a)	UK LFS	Couples by education	Partial	Cross-section
Frémeaux *et al.* (2024)	KLIPS panel	Couples + earnings	Partial	Annual
This paper (IBJ, JP)	IBJ platform logs	All actions	Yes	Monthly

Modeling Approach and Sample Coverage			
Paper	**Modeling Approach**	**Sample Size**	**Time Coverage**
Chiappori *et al.* (forthcoming)	CS extension (SEV)	140k marriages/yr	2011–2014
Chiappori *et al.* (2024)	Dupuy–Galichon	276 couples	2019
Abdellaoui *et al.* (2023)	SGAM (SES×genetics)	Tens of thousands	2000s–2010s
Almar and Schulz (2024)	k-means + CS	1.8M indiv./yr	1998–2018
Hoehn-Velasco and Penglase (2023)	SEV index	Millions	1993–2019
Shiue and Keller (2022)	Sorting indices	14k+ marriages	1300–1900
Chiappori *et al.* (2025)	Axiomatic indices	100k+/cohort	1950s–1970s
Chiappori *et al.* (2020a)	CS-based index	297k indiv.	1945–1974
Frémeaux *et al.* (2024)	Earnings corr. + sim.	6.7k HHs	1998–2018
This paper (IBJ, JP)	Nonparametric matching	120k+ users	2014–2025

A.2 Summary Statistics (Omitted in the Main Text)

Unmatched Users Table 12 also reports the summary statistics of unmatched users. Compared to their matched counterparts, unmatched individuals differ most notably in educational attainment and household preferences. Unmatched men and women are less educated on average: 66.9% of unmatched men and 64.6% of unmatched women hold undergraduate or graduate degrees, compared to 79.7% and 68.7%, respectively, among matched individuals. Additionally, unmatched men are more likely to smoke regularly (6.9% vs. 3.4%) but less likely to drink regularly (22.3% vs. 26.2%), suggesting a distinct lifestyle profile relative to matched men. Differences in household attitudes are also present: unmatched women are somewhat less likely to report taking primary responsibility for housework ("Do It Myself": 7.8% unmatched vs. 9.1% matched), and unmatched men are less likely to report wanting children (62.0% unmatched vs. 70.7% matched). These patterns indicate that both observable human capital and alignment in household preferences may play a role in selection into match.

Table 12: Summary Statistics in 2024 by Gender: Unmatched

(a) Continuous

Gender		N	mean	median	sd	min	max
female	Age	19885	37.39	36.00	8.42	20.00	85.00
	Income (upper limit)	19631	499.08	500.00	220.23	300.00	2100.00
	Height	19883	158.88	158.00	5.28	142.00	182.00
	Weight	19881	49.42	50.00	7.13	35.00	95.00
	Flexibility	19824	-0.18	-0.19	0.50	-1.45	1.12
male	Age	14307	41.45	40.00	9.68	20.00	91.00
	Income (upper limit)	14263	700.05	600.00	345.59	300.00	2100.00
	Height	14306	171.17	170.00	5.84	142.00	196.00
	Weight	14306	66.33	65.00	10.65	35.00	95.00
	Flexibility	14237	-0.19	-0.21	0.35	-1.45	0.90

(b) Discrete

		female		male	
		N	Pct.	N	Pct.
Educational level	(1)JuniorHigh	60	0.3	125	0.9
	(2)HighSchool	1973	9.9	2661	18.5
	(3)Vocational	4845	24.3	1719	12.0
	(4)Undergraduate	11612	58.2	7514	52.3
	(5)Graduate	1285	6.4	2105	14.6
	NA	194	1.0	247	1.7
Drink Alcohol level	(1)Never	4176	20.9	2223	15.5
	(2)SocialOnly	12983	65.0	8876	61.8
	(3)DrinkRegularly	2715	13.6	3200	22.3
	NA	95	0.5	72	0.5
Smoking level	(1)Never	19615	98.2	12716	88.5
	(2)Occasionally	126	0.6	597	4.2
	(3)Regularly	133	0.7	986	6.9
	NA	95	0.5	72	0.5
Marital History Dummy	(1)NeverMarried	17220	86.2	11844	82.4
	(2)DivorcedOrWidowed	2657	13.3	2456	17.1
	NA	92	0.5	71	0.5
Housework Share Level	(1)LeaveToPartner	17	0.1	102	0.7
	(2)DiscussWithPartner	5742	28.8	3364	23.4
	(3)ShareEqually	10174	50.9	8316	57.9
	(4)DoItMyself	1553	7.8	553	3.8
	NA	2483	12.4	2036	14.2
Child Care Share Level	(1)DoNotWantChildren	953	4.8	340	2.4
	(2)LeaveToPartner	6	0.0	43	0.3
	(3)DiscussWithPartner	5257	26.3	3445	24.0
	(4)ShareEqually	9679	48.5	7846	54.6
	(5)DoItMyself	1197	6.0	532	3.7
	NA	2877	14.4	2165	15.1
Desired Child Dummy	(1)DoNotWant	1887	9.4	695	4.8
	(2)NoPreference	5047	25.3	4659	32.4
	(3)Want	12923	64.7	8912	62.0
	NA	112	0.6	105	0.7

B Additional Results

B.1 Estimation Details of Many-to-many Matching Model in Section 4.4

Let $t \in \mathcal{T} = \{\text{Application}, \text{Pre-relationship}, \text{Serious relationship}, \text{Proposal}\}$ index stages of the IBJ pipeline.[22] A *trade* at stage t is a directed or undirected relationship event between a male m and a female w that is observed at that stage (e.g., an application sent/received; entry into Pre-relationship; transition to Serious relationship; and final Proposal/engagement). Let Ω_t be the finite set of feasible stage-t trades in a given market-period. Each trade $\omega \in \Omega_t$ identifies (i) a buyer-side observable type $b(\omega)$ and (ii) a seller-side observable type $s(\omega)$ in Fox (2018)'s notation; here we fix the sides to be male and female for expositional clarity:

$$b(\omega) = m, \qquad s(\omega) = w.$$

A realized stage-t outcome is a (multi-)set of trades, which we denote by $M_t \subseteq \Omega_t$. The model allows many-to-many outcomes: a man can be involved in multiple trades at stages prior to final commitment, and likewise for a woman.

Let an agent i (male or female) choose a set of trades as a buyer $\Phi \subseteq \Omega_t$ and as a seller $\Psi \subseteq \Omega_t$. We restrict attention to the two-sided case in which males participate only on one side and females on the other, so each agent's feasible portfolio is one-sided, but we keep Fox (2018)'s notation to emphasize the generality.[23] Agent i's profit from portfolio (Φ, Ψ) at stage t is

$$\pi_{it}(\Phi, \Psi) = v_{it}(\Phi, \Psi) - \sum_{\omega \in \Phi} p_{\omega t} + \sum_{\omega \in \Psi} p_{\omega t}, \tag{10}$$

where $p_{\omega t}$ is the (unobserved) transfer/price for trade ω at stage t.

We specify the deterministic component of valuations using observables only (as required by Assumption 1 in Fox (2018)):

$$v_{it}(\Phi, \Psi) = \pi_{\theta_t}\big(j(i), \Phi, \Psi\big) + \varepsilon_{it}(\Phi, \Psi), \tag{11}$$

where $j(i)$ is an observable agent type (or an observable bin), θ_t is a stage-specific parameter vector, and $\varepsilon_{it}(\Phi, \Psi)$ is an idiosyncratic component.

An allocation B_t assigns to each observable type j a distribution over portfolios (Φ, Ψ). A competitive equilibrium (B_t, p_t) at stage t consists of an incentive-compatible allocation and a price vector $p_t = (p_{\omega t})_{\omega \in \Omega_t}$ such that all trades clear (zero excess demand), as in the matching-with-trading-networks model of Azevedo and Hatfield (2018). Under standard regularity conditions,

[22] We use the index t both to denote calendar time (years) when studying long-run trends at the Proposal stage, and to denote stages of the matching pipeline when analyzing within-pipeline dynamics. While this constitutes a mild abuse of notation, the two uses are conceptually distinct: the former captures temporal evolution across cohorts, whereas the latter captures progression across relationship stages within a given cohort.

[23] In Fox (2018), a full agent type i has a valuation $v_i(\Phi, \Psi)$ over the sets of trades where the agent is a buyer and a seller. In our two-sided restriction, one of the two sets is empty by construction for each gender.

equilibrium exists and is generically unique in the aggregate.[24]

Identification Following Assumption 2 of Fox (2018), we assume that the parameter space of θ_t is compact, the distribution of $\varepsilon_{it}(\cdot)$ is exchangeable within $j(i)$, allowing heteroskedasticity across $j(i)$, $\varepsilon_{it}(\cdot)$ has a full support, and the observations (Φ_i, Ψ_i) for $i = 1, \ldots, N$ agents are independent and identically distributed (i.i.d.). This assumption underlies the rank-order property that delivers (set) identification in matching maximum score, and it is the same key restriction highlighted in Fox (2018).

Estimation Let $\mathcal{G}_t$ be a researcher-chosen set of feasible *local deviations* (inequalities) at stage t. Each inequality compares the realized configuration of two trades $\Omega_g = \{\omega_1, \omega_2\}$ to an alternative configuration $\bar{\Omega}_g = \{\omega_3, \omega_4\}$ that preserves the multiset of observable types on both sides. We further restrict the deterministic component to be linear in the parameters θ_t, i.e.,

$$\pi_{\theta_t}\big(j(i), \Phi, \Psi\big) = X_t(j(i), \Phi, \Psi)^\top \theta_t.$$

For each inequality $g \in \mathcal{G}_t$, define

$$Z_{gt}(\theta_t) = \sum_{\omega \in \Omega_g} X_t(\omega)^\top \theta_t - \sum_{\omega \in \bar{\Omega}_g} X_t(\omega)^\top \theta_t,$$

where $X_t(\omega)$ denotes the vector of observable trade features derived from the matching induced by $\omega = (m, w)$, so $X_t(\omega)^\top \theta_t$ is the corresponding scalar deterministic surplus contribution. In the pairwise specification adopted below, these features reduce to bilinear interactions between male and female attributes. The matching maximum score objective at stage t is

$$Q_t(\theta_t) = \sum_{g \in \mathcal{G}_{t,N}} \mathbf{1}\{Z_{gt}(\theta_t) \geq 0\}, \tag{12}$$

where $\mathcal{G}_{t,N}$ is the set of inequalities that are *realized/sampled* in the data for stage t. Under the rank-order property, maximizers of $Q_t(\theta_t)$ deliver a (set-)consistent estimator of θ_t for each stage. We follow Fox (2018) by sampling a computationally feasible subset of inequalities at each stage and relying on set identification when the implied support conditions for point identification fail.

To connect the Fox estimator to interpretable assortativeness objects, we choose $X_t(\omega)$ to include *bilinear interactions* between male and female continuous attributes x_m and y_w. Specifically, for a trade $\omega = (m, w)$ at stage t, let

$$X_t(\omega) = \mathrm{vec}\big(x_m y_w^\top\big), \qquad \theta_t = \mathrm{vec}(A_t), \tag{13}$$

[24] See Fox (2018) and Azevedo and Hatfield (2018) for the trading networks equilibrium conditions and the generic uniqueness discussion.

so that the systematic component of a single trade's surplus is

$$x_m^\top A_t y_w.$$

The $d \times d$ matrix A_t is a stage-specific *affinity matrix* whose diagonal elements represent assortativeness on each attribute and whose off-diagonal elements represent cross-attribute complementarities/substitutabilities.

Estimating A_t separately by stage provides a stage-specific decomposition of sorting: early stages capture assortativeness in initiation and screening (Application), while later stages capture assortativeness conditional on having passed earlier-stage filters (Pre-relationship, Serious relationship, Proposal). Throughout, we treat each stage as a separate matching market with its own equilibrium object and identify θ_t from within-stage local deviations.

A Many-to-Many TU Matching Model: Full Interaction Results Tables 13 and 14 compare the baseline specification in Table 10 that restricts attention to diagonal elements of the affinity matrix with a more flexible full-interaction model that allows for cross-attribute complementarities. Relative to the diagonal specification, the full-interaction model substantially increases the number of parameters to be estimated, and as expected in a semiparametric matching maximum score framework (Fox 2018, Manski 1975), many interaction terms are weakly identified, with wide confidence intervals that frequently include zero. This reflects a general limitation of rank-based estimators (Manski 1975): as the parameter dimension grows, point identification becomes increasingly difficult and the identified set expands for many coefficients. Importantly, however, the key diagonal patterns for age, income, and preferences for children remain robustly positive across specifications. Marital-history assortativeness remains positive in point estimates, but it is estimated less precisely in the later stages under the full-interaction model. These results suggest that the main qualitative conclusions from the diagonal specification are not driven by omitted cross-attribute interactions, while also underscoring the precision costs of the richer parameterization. Given the limited additional insight provided by the full-interaction terms and the loss of precision associated with higher-dimensional parameterization, the diagonal specification offers a parsimonious and robust summary of assortative matching in the data.

Table 13: Matching Maximum Score Estimation: Full Interaction Model

(a) Application

	Education	Age	Income	Flexibility	Height	Weight	Drink	Smoke	Marital History	Housework	Childcare	Child
Education	1.00	-3.59	5.63	3.78	0.93	0.53	3.92	-2.35	-1.91	2.35	1.52	4.12
	[1.00, 1.00]	[-9.35, 4.19]	[-0.72, 9.78]	[-6.50, 9.67]	[-6.81, 8.11]	[-6.63, 8.70]	[-5.98, 9.83]	[-9.42, 6.34]	[-8.30, 4.90]	[-5.38, 9.64]	[-8.89, 9.64]	[-3.81, 9.56]
Age	-5.08	9.28	5.42	1.96	3.76	3.89	-4.81	-0.75	6.36	1.55	-5.04	-4.89
	[-9.77, 1.04]	[8.06, 10.00]	[-0.65, 9.88]	[-6.62, 7.99]	[-3.41, 9.54]	[-2.64, 9.17]	[-9.78, 1.85]	[-9.78, 9.44]	[-1.01, 9.87]	[-7.03, 8.46]	[-9.92, 1.13]	[-9.98, 4.18]
Income	5.05	2.57	7.74	-4.30	-3.72	-5.69	-0.57	0.51	3.32	0.49	0.29	4.39
	[-1.26, 9.74]	[-6.25, 9.65]	[3.31, 9.89]	[-9.38, 4.81]	[-9.40, 2.81]	[-9.96, 1.91]	[-9.92, 7.57]	[-8.65, 9.22]	[-6.48, 9.66]	[-7.57, 9.32]	[-8.31, 8.35]	[-7.00, 9.93]
Flexibility	0.83	3.88	-2.07	2.04	-3.13	1.27	4.10	1.12	-2.24	-1.39	3.42	1.79
	[-8.27, 8.74]	[-3.66, 9.49]	[-8.33, 5.21]	[-8.95, 9.52]	[-9.69, 6.54]	[-6.04, 8.91]	[-0.97, 8.97]	[-8.10, 9.46]	[-9.65, 6.97]	[-8.91, 6.25]	[-4.37, 9.42]	[-8.58, 9.52]
Height	-0.39	-5.21	6.09	-2.55	3.33	0.76	-1.19	-2.57	3.25	3.30	1.13	-0.87
	[-8.98, 6.61]	[-9.88, 1.42]	[-1.52, 9.82]	[-8.43, 8.35]	[-3.76, 9.15]	[-8.56, 9.04]	[-8.23, 7.43]	[-9.43, 6.50]	[-5.73, 9.62]	[-3.46, 9.04]	[-6.86, 9.54]	[-9.51, 7.28]
Weight	-5.02	1.09	-0.52	1.20	4.83	2.70	0.47	-0.42	-2.48	1.63	-2.23	1.22
	[-9.70, 1.29]	[-8.03, 8.93]	[-8.14, 7.33]	[-7.40, 6.44]	[-4.25, 9.90]	[-6.43, 9.16]	[-7.78, 8.36]	[-8.16, 9.64]	[-9.33, 7.25]	[-7.56, 9.26]	[-9.59, 7.80]	[-9.75, 9.24]
Drink	-2.73	-0.71	2.44	1.76	-3.66	0.92	7.71	1.48	2.35	-1.89	0.54	0.78
	[-9.13, 6.05]	[-9.15, 9.19]	[-6.46, 9.62]	[-7.24, 8.20]	[-9.37, 4.55]	[-8.31, 8.89]	[3.94, 9.62]	[-8.07, 9.57]	[-6.50, 8.68]	[-8.46, 7.76]	[-7.95, 8.43]	[-7.56, 8.51]
Smoke	-1.60	1.06	-3.16	-0.86	-0.99	0.11	2.44	2.04	1.57	-2.91	-2.06	-1.65
	[-9.60, 9.64]	[-8.43, 7.95]	[-9.68, 6.90]	[-8.16, 7.78]	[-8.55, 9.33]	[-7.91, 9.05]	[-9.32, 8.57]	[-8.64, 9.21]	[-7.63, 9.40]	[-9.19, 7.20]	[-8.99, 5.98]	[-8.90, 7.65]
Marital History	-1.12	5.11	2.45	0.70	-1.46	-2.50	-2.30	-0.58	6.28	-0.85	-1.38	-2.45
	[-9.35, 8.33]	[-3.68, 9.73]	[-4.32, 9.44]	[-8.52, 8.71]	[-9.00, 6.63]	[-9.35, 6.31]	[-9.03, 7.08]	[-8.88, 9.06]	[0.70, 9.80]	[-8.62, 9.25]	[-8.82, 7.83]	[-9.47, 5.52]
Housework	1.25	-1.30	-0.21	-1.47	-1.44	1.47	1.14	0.32	0.97	3.17	0.15	-0.82
	[-7.62, 9.68]	[-9.54, 8.79]	[-8.65, 9.15]	[-9.34, 6.79]	[-9.10, 6.54]	[-7.75, 9.23]	[-7.75, 8.18]	[-9.60, 9.06]	[-7.43, 8.53]	[-4.87, 9.47]	[-8.49, 7.51]	[-7.96, 6.20]
Childcare	0.39	-4.91	-0.28	-2.47	-3.73	-0.50	1.26	-1.49	-1.29	-0.24	1.33	2.84
	[-8.58, 7.22]	[-9.78, 1.74]	[-7.26, 8.48]	[-9.56, 6.29]	[-9.60, 6.08]	[-7.85, 6.93]	[-8.82, 8.01]	[-8.47, 7.25]	[-8.90, 9.05]	[-8.51, 5.85]	[-8.59, 9.27]	[-7.23, 9.76]
Child	1.63	-7.45	2.86	1.18	0.08	0.29	-1.12	-1.53	-0.85	-0.87	3.23	6.97
	[-7.63, 9.19]	[-9.76, -2.27]	[-8.26, 9.83]	[-8.15, 9.60]	[-8.04, 8.90]	[-8.18, 7.38]	[-8.84, 8.41]	[-9.81, 9.45]	[-9.86, 9.18]	[-8.58, 6.96]	[-5.07, 9.08]	[2.88, 9.75]

(b) Pre-relation

	Education	Age	Income	Flexibility	Height	Weight	Drink	Smoke	Marital History	Housework	Childcare	Child
Education	1.00	-5.46	6.48	3.12	3.49	-2.99	-0.95	-2.76	-1.30	-2.32	-0.43	0.88
	[1.00, 1.00]	[-9.74, -0.32]	[1.82, 9.94]	[-4.45, 9.54]	[-3.66, 9.17]	[-9.67, 7.80]	[-9.08, 9.10]	[-9.69, 8.44]	[-9.40, 8.11]	[-8.77, 5.90]	[-8.44, 7.95]	[-5.76, 7.86]
Age	-4.92	9.15	2.85	1.13	1.93	2.82	-2.08	1.95	4.56	-4.01	-4.69	-5.81
	[-9.57, 2.62]	[8.21, 9.97]	[-6.96, 9.85]	[-7.10, 9.22]	[-8.40, 8.51]	[-4.65, 9.59]	[-9.59, 6.45]	[-6.54, 9.57]	[-3.13, 9.72]	[-9.51, 3.74]	[-9.88, 4.96]	[-9.77, 0.06]
Income	5.98	4.25	7.56	-3.49	2.77	-5.18	0.74	-1.73	-0.44	-1.61	1.71	0.90
	[-1.91, 9.71]	[-6.20, 9.68]	[3.51, 9.82]	[-9.41, 6.75]	[-8.45, 9.80]	[-9.31, 3.65]	[-8.39, 7.96]	[-9.38, 6.59]	[-8.23, 8.21]	[-8.71, 7.84]	[-9.06, 9.58]	[-9.20, 9.36]
Flexibility	-1.61	2.50	-2.74	4.09	-4.00	0.77	-0.94	-0.68	-0.83	0.32	-0.42	-2.22
	[-8.75, 9.27]	[-6.82, 9.41]	[-9.49, 6.38]	[-5.57, 9.37]	[-9.70, 4.58]	[-7.09, 7.91]	[-7.02, 9.17]	[-9.50, 6.66]	[-9.15, 7.84]	[-6.25, 6.78]	[-9.12, 7.88]	[-9.83, 5.65]
Height	-2.64	-3.33	3.52	-0.92	5.34	-3.67	3.87	-0.14	1.59	-1.93	-2.40	0.05
	[-9.11, 5.01]	[-9.12, 5.88]	[-5.71, 9.37]	[-7.85, 5.00]	[-1.04, 9.86]	[-9.66, 4.73]	[-2.65, 8.79]	[-9.42, 7.67]	[-7.21, 9.42]	[-9.24, 7.77]	[-9.62, 7.76]	[-8.55, 8.24]
Weight	-3.04	3.13	-1.48	2.13	2.86	7.21	0.19	2.24	1.12	2.36	3.57	-0.64
	[-8.72, 3.11]	[-4.33, 8.72]	[-9.18, 7.89]	[-6.18, 8.79]	[-8.20, 9.50]	[2.50, 9.91]	[-9.54, 8.30]	[-6.59, 9.43]	[-8.73, 8.83]	[-8.20, 8.85]	[-4.08, 9.70]	[-9.32, 8.75]
Drink	1.55	-0.16	4.11	4.45	0.55	1.92	5.38	-0.39	-1.99	-2.24	3.92	-0.88
	[-8.86, 7.51]	[-9.11, 7.94]	[-2.25, 9.76]	[-3.41, 9.30]	[-7.76, 7.65]	[-6.91, 9.25]	[-0.42, 9.23]	[-9.25, 8.66]	[-9.79, 4.76]	[-9.44, 5.41]	[-3.93, 9.40]	[-8.34, 8.41]
Smoke	-0.79	0.51	-0.65	1.78	1.14	-0.24	1.24	-0.68	-1.50	0.18	0.21	-2.26
	[-9.29, 8.35]	[-9.51, 8.88]	[-8.44, 8.24]	[-6.18, 9.68]	[-6.26, 9.10]	[-8.46, 7.21]	[-7.95, 8.29]	[-9.34, 8.77]	[-8.99, 8.75]	[-9.17, 7.65]	[-8.55, 9.15]	[-8.90, 6.59]
Marital History	-2.02	6.61	4.21	2.59	-1.45	0.43	2.40	-0.20	5.74	-0.87	-2.01	-0.10
	[-8.36, 6.89]	[0.11, 9.93]	[-7.98, 9.33]	[-5.87, 8.91]	[-8.71, 6.67]	[-8.71, 8.48]	[-8.02, 8.07]	[-9.58, 9.79]	[0.46, 9.51]	[-9.29, 8.11]	[-9.00, 7.45]	[-8.14, 8.87]
Housework	-1.09	1.38	3.03	-1.51	-0.08	3.22	-4.19	0.66	3.11	2.81	-0.43	-2.36
	[-9.41, 8.43]	[-6.55, 8.25]	[-6.77, 9.38]	[-9.35, 5.63]	[-9.22, 6.64]	[-5.75, 8.67]	[-9.72, 5.65]	[-7.30, 9.59]	[-4.49, 9.13]	[-5.33, 9.74]	[-9.14, 7.99]	[-9.35, 7.28]
Childcare	-2.08	-2.41	1.03	-1.09	0.42	-2.25	1.11	-0.56	1.19	-1.02	1.88	4.45
	[-8.73, 6.88]	[-9.47, 6.73]	[-8.65, 9.50]	[-9.59, 8.80]	[-8.52, 8.10]	[-9.16, 4.60]	[-8.59, 9.56]	[-9.47, 8.00]	[-8.67, 8.53]	[-9.19, 8.37]	[-7.17, 9.50]	[-4.18, 9.62]
Child	1.10	-7.32	2.24	-0.87	-0.97	-1.49	2.47	-1.03	-3.47	-1.66	3.33	7.39
	[-4.41, 8.94]	[-9.71, -2.32]	[-5.46, 9.22]	[-9.43, 7.30]	[-9.42, 7.79]	[-7.14, 5.12]	[-6.04, 9.45]	[-9.05, 8.91]	[-9.64, 4.63]	[-9.00, 6.69]	[-6.61, 9.42]	[4.00, 9.75]

Note: See the details in the main text.

Table 14: Matching Maximum Score Estimation: Full Interaction Model

(a) Serious Relation

	Education	Age	Income	Flexibility	Height	Weight	Drink	Smoke	Marital History	Housework	Childcare	Child
Education	1.00	-3.69	5.98	-1.99	0.13	-3.92	3.35	-1.18	1.06	-0.33	-0.86	2.80
	[1.00, 1.00]	[-8.86, 6.45]	[-0.54, 9.90]	[-9.12, 5.86]	[-8.08, 9.62]	[-9.39, 2.17]	[-6.40, 9.16]	[-9.70, 8.74]	[-6.93, 9.06]	[-8.33, 8.75]	[-9.39, 7.95]	[-6.44, 9.54]
Age	-4.89	9.50	4.01	2.58	2.52	1.87	-0.33	-1.18	5.37	-2.07	-5.07	-6.10
	[-9.53, 3.09]	[8.20, 9.99]	[-3.61, 9.78]	[-8.28, 9.24]	[-4.73, 9.21]	[-8.40, 9.20]	[-9.02, 7.88]	[-9.15, 7.83]	[-1.89, 9.76]	[-8.72, 7.19]	[-9.73, -0.35]	[-9.87, -0.41]
Income	4.39	2.80	7.22	-1.20	2.66	-6.25	1.29	1.34	2.81	-0.86	2.26	-0.49
	[-4.82, 9.92]	[-7.83, 9.22]	[2.13, 9.88]	[-9.20, 6.20]	[-5.11, 9.68]	[-9.70, 0.59]	[-7.22, 9.33]	[-9.03, 9.28]	[-7.28, 8.80]	[-8.58, 7.98]	[-6.68, 9.07]	[-7.49, 7.57]
Flexibility	2.53	3.82	-2.60	1.76	0.72	3.93	1.45	1.43	1.32	2.70	1.90	1.51
	[-7.35, 9.89]	[-3.15, 9.68]	[-8.68, 4.16]	[-5.91, 8.64]	[-6.61, 8.01]	[-3.64, 9.60]	[-7.40, 8.61]	[-7.88, 8.60]	[-7.75, 9.46]	[-4.10, 8.83]	[-6.80, 8.81]	[-8.20, 8.97]
Height	3.69	-2.10	3.78	-1.50	6.33	-3.44	3.41	0.58	-2.01	-3.33	1.02	1.89
	[-3.31, 9.64]	[-7.88, 4.21]	[-4.90, 9.48]	[-7.75, 5.82]	[1.10, 9.76]	[-9.71, 4.25]	[-3.55, 9.33]	[-7.99, 9.22]	[-9.71, 7.57]	[-9.81, 3.69]	[-7.21, 8.83]	[-5.93, 9.23]
Weight	-1.09	4.70	-3.91	0.04	0.85	6.52	1.43	1.67	-0.73	-2.50	-1.44	-0.66
	[-8.04, 7.35]	[-2.65, 9.52]	[-9.68, 3.58]	[-9.74, 7.81]	[-8.98, 8.06]	[-0.33, 9.89]	[-6.00, 8.05]	[-9.11, 8.10]	[-8.59, 8.51]	[-9.12, 6.09]	[-9.74, 7.74]	[-9.17, 8.89]
Drink	1.69	-0.71	3.98	-1.20	1.97	1.99	7.09	-0.89	2.25	-1.32	-1.64	1.22
	[-7.13, 7.81]	[-6.89, 7.90]	[-4.45, 9.66]	[-8.33, 7.05]	[-7.05, 8.07]	[-6.30, 8.60]	[1.33, 9.80]	[-9.15, 8.28]	[-7.72, 9.30]	[-8.90, 6.30]	[-9.07, 6.36]	[-7.19, 8.41]
Smoke	-3.15	3.52	-2.76	-0.10	-1.29	-3.00	0.52	3.00	1.16	-0.02	0.83	-1.33
	[-9.22, 4.89]	[-5.04, 9.87]	[-8.94, 6.31]	[-9.45, 9.33]	[-8.99, 5.32]	[-9.64, 7.70]	[-8.14, 9.70]	[-5.76, 9.44]	[-8.30, 8.81]	[-8.74, 9.49]	[-8.85, 8.47]	[-8.56, 7.63]
Marital History	-2.91	5.61	3.65	1.90	0.59	1.36	-0.22	1.58	4.74	0.37	-0.28	-3.30
	[-9.27, 5.91]	[-2.37, 9.68]	[-2.93, 9.71]	[-3.80, 9.37]	[-7.08, 8.75]	[-7.27, 8.90]	[-8.33, 8.24]	[-9.05, 9.35]	[-2.74, 9.17]	[-8.50, 9.20]	[-9.75, 8.60]	[-9.87, 3.40]
Housework	-1.58	1.77	5.02	-0.17	1.09	0.08	0.24	-1.65	1.92	3.68	0.68	-1.63
	[-9.07, 5.51]	[-8.81, 9.41]	[-3.97, 9.33]	[-8.24, 8.57]	[-8.83, 9.12]	[-8.94, 8.51]	[-8.04, 8.59]	[-9.48, 8.99]	[-7.44, 8.35]	[-4.91, 9.68]	[-8.37, 8.43]	[-9.46, 6.81]
Childcare	-2.18	-1.90	-0.22	-1.82	-1.36	0.30	2.10	-0.93	-1.83	2.45	2.74	4.63
	[-8.76, 6.18]	[-8.99, 5.20]	[-8.68, 8.50]	[-7.58, 5.12]	[-8.79, 7.21]	[-8.91, 8.56]	[-5.85, 8.05]	[-9.21, 9.41]	[-9.21, 5.49]	[-6.38, 9.31]	[-4.99, 9.79]	[-3.02, 9.46]
Child	1.49	-6.50	3.93	0.47	0.33	-3.00	1.19	1.60	-1.53	1.69	5.22	6.92
	[-6.88, 9.33]	[-9.84, -2.76]	[-2.72, 9.43]	[-7.29, 8.76]	[-8.25, 8.71]	[-9.68, 6.34]	[-6.65, 7.80]	[-7.47, 9.72]	[-8.90, 9.00]	[-6.10, 9.11]	[-3.42, 9.95]	[1.77, 9.89]

(b) Proposal

	Education	Age	Income	Flexibility	Height	Weight	Drink	Smoke	Marital History	Housework	Childcare	Child
Education	1.00	-4.58	6.75	0.54	2.60	-2.63	2.67	-1.61	-2.39	1.92	2.76	0.93
	[1.00, 1.00]	[-9.63, 0.50]	[2.26, 9.49]	[-8.24, 8.27]	[-7.87, 9.35]	[-9.06, 6.63]	[-4.62, 9.61]	[-9.51, 7.98]	[-9.76, 5.85]	[-6.46, 8.60]	[-6.84, 9.58]	[-6.24, 8.85]
Age	-5.65	9.11	3.07	0.93	2.25	-0.32	-2.68	0.26	5.62	-1.88	-4.68	-5.42
	[-9.81, 0.97]	[7.61, 9.92]	[-6.79, 9.88]	[-7.58, 8.00]	[-5.18, 9.22]	[-8.17, 8.76]	[-9.73, 7.56]	[-9.48, 9.25]	[-1.93, 9.96]	[-9.23, 8.47]	[-9.88, 6.96]	[-9.89, -0.62]
Income	3.68	2.29	7.48	-3.57	2.45	-7.24	5.67	1.07	3.15	1.67	1.97	3.79
	[-2.74, 8.89]	[-5.83, 9.35]	[2.44, 9.91]	[-9.08, 7.62]	[-7.67, 8.19]	[-9.78, -2.50]	[-3.49, 9.94]	[-8.62, 9.65]	[-3.05, 8.53]	[-6.78, 9.08]	[-7.31, 9.10]	[-5.47, 9.58]
Flexibility	2.22	3.12	1.59	1.04	0.28	0.39	2.19	0.21	-2.34	-1.96	-0.85	-0.62
	[-7.78, 9.36]	[-5.30, 8.77]	[-6.98, 9.55]	[-8.71, 7.90]	[-8.35, 9.74]	[-7.94, 7.96]	[-5.52, 9.11]	[-8.40, 9.20]	[-9.27, 7.02]	[-9.09, 5.37]	[-8.70, 7.91]	[-7.60, 9.22]
Height	-1.30	0.56	2.41	-1.26	7.39	-2.53	-0.47	-1.60	1.47	0.21	0.28	4.87
	[-9.47, 7.70]	[-9.44, 8.91]	[-6.33, 8.76]	[-8.29, 7.79]	[1.47, 9.93]	[-9.11, 4.66]	[-8.39, 7.88]	[-9.71, 7.34]	[-8.12, 7.88]	[-8.39, 7.58]	[-9.29, 8.08]	[-2.76, 9.51]
Weight	-0.20	4.89	0.73	-5.06	5.05	6.88	-0.63	-0.42	-0.43	2.79	2.28	2.51
	[-8.33, 6.86]	[-3.25, 9.22]	[-8.16, 9.42]	[-9.37, 1.17]	[-1.29, 9.98]	[2.03, 9.86]	[-8.35, 5.83]	[-8.85, 8.30]	[-9.42, 9.10]	[-4.98, 9.74]	[-7.24, 9.06]	[-6.77, 9.40]
Drink	1.86	-2.52	2.22	-1.95	0.20	-4.05	7.52	1.18	2.70	1.01	-2.39	-0.31
	[-9.02, 7.76]	[-9.77, 6.90]	[-6.89, 9.32]	[-9.60, 6.17]	[-9.04, 7.75]	[-9.85, 3.63]	[4.15, 9.83]	[-8.33, 9.52]	[-2.97, 8.45]	[-8.07, 8.95]	[-9.24, 5.52]	[-7.52, 9.09]
Smoke	-2.91	4.26	-0.96	2.07	1.80	1.02	4.02	2.62	1.35	-3.57	0.76	-2.16
	[-9.12, 7.71]	[-6.45, 9.60]	[-8.96, 8.68]	[-5.13, 9.73]	[-8.31, 9.83]	[-6.76, 8.34]	[-6.55, 9.74]	[-6.79, 9.76]	[-8.93, 8.00]	[-9.80, 2.67]	[-8.20, 9.12]	[-8.88, 5.31]
Marital History	-4.07	6.32	3.60	-2.41	0.45	-3.01	5.11	1.08	5.62	-1.28	-3.40	-1.65
	[-9.77, 2.91]	[0.19, 9.83]	[-3.28, 9.58]	[-9.72, 6.31]	[-6.43, 8.66]	[-9.85, 8.85]	[-2.48, 9.66]	[-9.59, 9.24]	[-1.47, 9.82]	[-9.15, 8.13]	[-9.80, 5.25]	[-9.29, 8.09]
Housework	-0.32	-2.46	-0.34	0.82	1.65	0.49	1.30	-0.67	3.16	-2.71	-0.13	1.37
	[-8.53, 9.21]	[-9.66, 5.29]	[-9.12, 9.27]	[-6.21, 8.33]	[-8.75, 9.54]	[-7.63, 8.22]	[-8.83, 9.24]	[-8.94, 8.98]	[-5.49, 9.58]	[-9.01, 5.20]	[-9.40, 8.10]	[-6.99, 9.10]
Childcare	-0.83	-3.84	-0.51	-1.50	-1.43	1.35	-1.73	-0.19	0.02	3.48	1.47	3.23
	[-9.67, 9.02]	[-9.82, 4.18]	[-9.43, 7.91]	[-8.15, 7.97]	[-9.04, 7.01]	[-8.39, 9.06]	[-9.18, 9.44]	[-8.89, 8.45]	[-9.06, 7.43]	[-6.22, 9.02]	[-4.45, 7.95]	[-4.20, 8.92]
Child	-0.30	-6.64	0.19	-0.34	-2.02	-1.18	-1.78	-2.17	-4.13	2.73	5.27	6.67
	[-9.57, 8.07]	[-9.96, -0.14]	[-8.71, 6.89]	[-8.93, 7.26]	[-8.86, 7.65]	[-8.92, 6.78]	[-9.64, 6.61]	[-9.85, 8.01]	[-9.84, 6.24]	[-7.23, 9.65]	[-0.20, 9.49]	[0.41, 9.82]

Note: See the details in the main text.

B.2 Assortativeness in TU One-dimensional Discrete-Type Model (Choo and Siow 2006) in 2024

To highlight the dataset's granularity and novelty, we first apply the well-known framework of Choo and Siow (2006) to quantify assortative matching patterns and compare the contribution of each observed characteristic to match surplus.[25]

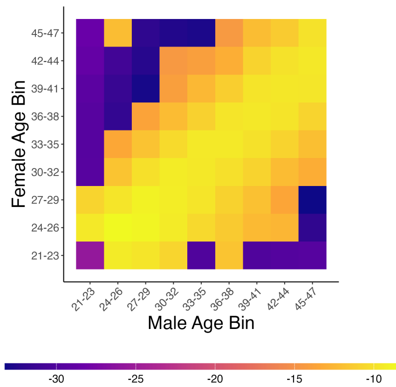
Anthropometric physical attractiveness Figure 9 displays the estimated systematic surplus $\hat{\Phi}_{ij}$ across joint bins of male and female attributes. Panel (a), which shows the results for age, reveals strong positive assortative matching: surplus is concentrated in a broad band near the diagonal, with the highest values occurring among women in their late 20s to mid-30s and men in their early 30s to late 30s. The ridge lies slightly above the exact diagonal for much of the support, consistent with a modest tendency for male partners to be somewhat older than female partners. Surplus declines as age differences widen, especially away from the dense central age bins. These results echo common patterns in marriage timing and are consistent with age-related preferences and fertility considerations.

Panels (b) through (d) in Figure 9 explore sorting based on physical characteristics. For height (Panel b), we observe strong positive assortative matching: taller men tend to match with taller women, and the surplus surface peaks along a diagonal ridge. In contrast, weight (Panel c) displays a more diffuse and asymmetric pattern, with several locally high-surplus cells rather than a single sharp diagonal. Panel (d) indicates that BMI-based sorting is more structured than weight-based sorting, with relatively high surplus concentrated in the upper-right portion of the matrix corresponding to higher BMI bins for both sexes. These findings suggest that physical appearance contributes to marital surplus in nuanced ways, with height being positively aligned and weight or BMI subject to more varied patterns.

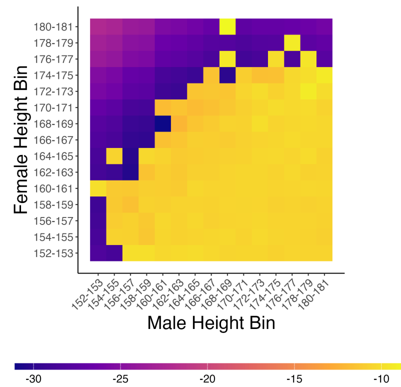
Sociodemographic attractiveness Panels (e) and (f) in Figure 9 depict sorting patterns on income and education, capturing sociodemographic dimensions of match surplus. The income plot reveals a clear positive gradient with respect to male income, while variation across female income is present but less monotone. The education panel shows that surplus is concentrated among pairings involving undergraduate and graduate categories, whereas cells involving junior-high education are consistently weak. These results highlight the salience of both economic capacity and educational alignment in shaping match gains in the marriage market.

Health and Lifestyle Preferences Panels (a) and (b) in Figure 10 present surplus estimates by drinking and smoking habits. These lifestyle traits exhibit modest but structured matching

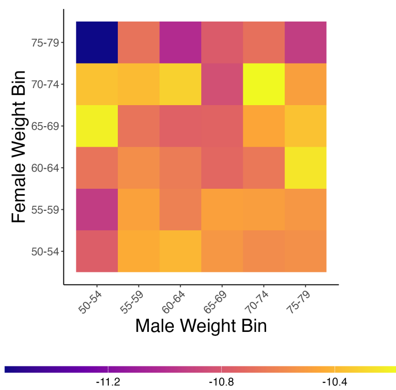
[25] Following Choo and Siow (2006), we estimate the total systematic surplus $\hat{\Phi}_{ij}$ using the relation $\mu_{ij}^2 = \mu_{i0}\mu_{0j}\exp(\Phi_{ij})$, where μ_{ij} is the number of matches between type-i men and type-j women, and μ_{i0}, μ_{0j} denote unmatched counts. Taking logs yields $\hat{\Phi}_{ij} = 2\log\mu_{ij} - \log\mu_{i0} - \log\mu_{0j}$. We compute μ_{ij} from observed engagements, and μ_{i0}, μ_{0j} from unmatched individuals in each type. To avoid undefined values, we replace zero counts with a small constant (10^{-8}). See deeper theoretical discussion in Galichon and Salanié (2022).



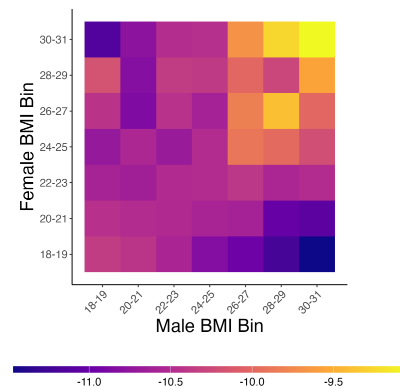
(a) Age



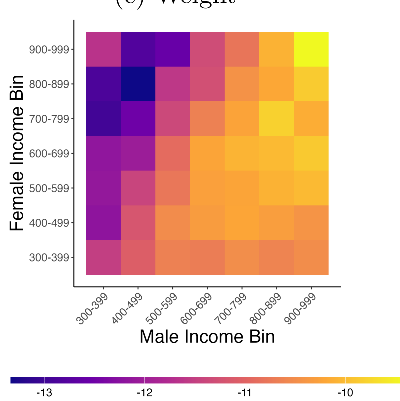
(b) Height



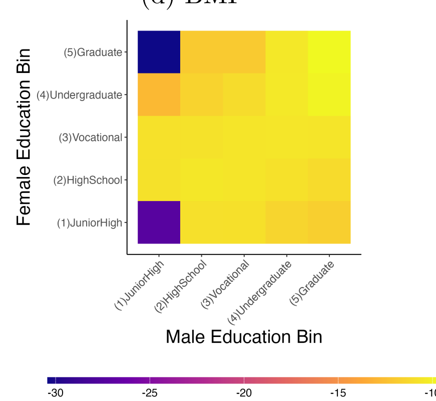
(c) Weight



(d) BMI



(e) Income Category



(f) Education

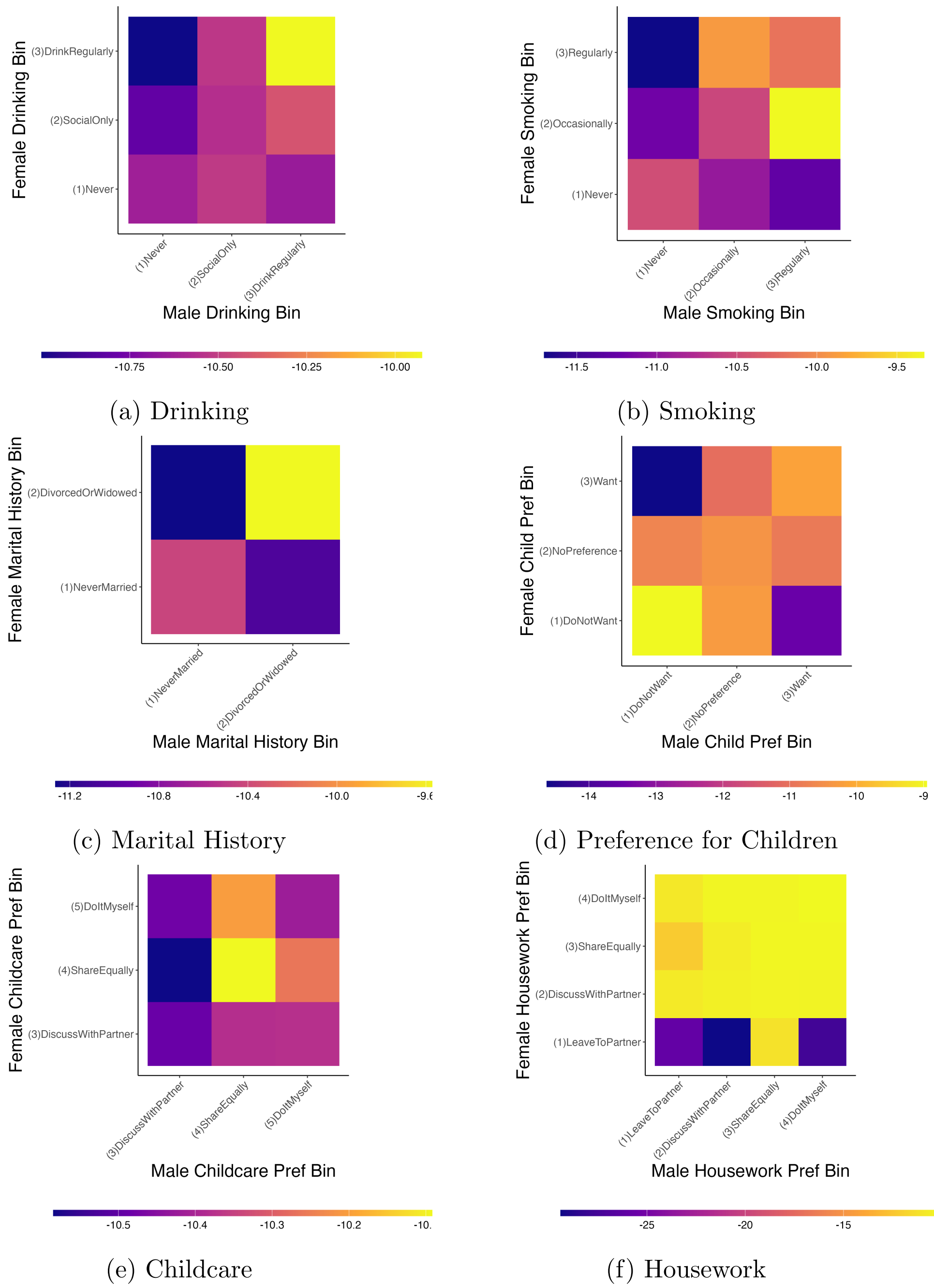
Figure 9: Systematic Surplus in Anthropometric and Sociodemographic Attractiveness

Note: Anthropometric physical attractiveness is captured by age, height, weight, and BMI. Sociodemographic attractiveness is captured by income and education. See Chiappori *et al.* (2012) and Dupuy and Galichon (2014) for discussion of the use of these characteristics.

patterns. For drinking, surplus tends to be higher among pairings involving regular drinkers than among pairs of non-drinkers. For smoking, the surface is not cleanly diagonal, and some off-diagonal combinations display relatively high surplus. While these factors do not dominate match surplus overall, they reflect nontrivial lifestyle-related complementarities or selection patterns that may influence long-term compatibility.

Marital History Panel (c) in Figure 10 focuses on marital history, distinguishing between never-married individuals and those who are divorced or widowed. The strongest surplus appears when both partners are previously married, while mixed-history pairings are weaker. This pattern suggests that shared life course trajectories along the remarriage margin may play an important role in perceived compatibility and in the structure of surplus.

Preferences over Family Formation Panels (d) through (f) in Figure 10 explore preferences related to family formation, including desire for children, childcare attitudes, and housework division. These surfaces show substantial structure, but the patterns differ across attributes. For desire for children, surplus is high at both ends of the alignment spectrum, with the strongest cell among couples where both report not wanting children and relatively high surplus also among couples where both report wanting children. Childcare attitudes display the clearest assortative pattern, with equal-sharing preferences generating the highest surplus. Housework preferences are more heterogeneous and less cleanly diagonal. Taken together, these figures suggest that family-related values matter for match surplus, but the relevant margin is not always simple like-with-like sorting.



(a) Drinking

(b) Smoking

(c) Marital History

(d) Preference for Children

(e) Childcare

(f) Housework

Figure 10: Systematic Surplus in Lifestyle, Marital History, and Family Preferences

Note: See Chiappori *et al.* (2018b) and Chiappori *et al.* (2024) for discussion of the use of smoking variables.