Marital Sorting on Pre-Marital Preferences for Household Behavior

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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 marriages is central to household economics and to analyzing the distributional consequences of household formation. A large body of literature 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, far less is known about how people sort on preferences that directly govern household behavior, such as the desire to have children or the willingness to engage in housework and childcare. These preferences fundamentally shape subsequent household decisions, including fertility, labor supply, and the allocation of time within households.[1]

A key challenge is that such preference measures are generally unavailable in the registry or census-type datasets commonly used to study marriage market sorting. Even when survey data collect information on preferences, observations are rarely available prior to marriage, limiting our ability to study sorting based on pre-marital traits. As a result, our understanding of which underlying preferences and characteristics are most salient in generating observed assortative matching remains incomplete.

This paper brings new evidence to this question using a uniquely rich dataset in which multiple household-relevant preferences are directly observed. Specifically, we analyze a novel dataset from IBJ, Japan's largest structured marriage matching platform. IBJ covers a non-negligible part of marriages in Japan; the dataset records over 10,000 confirmed engagements per year and accounts for approximately 3.3% of all new marriages in Japan 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), our unique data include individuals' preferences regarding having children and allocating time between market work and home after marriage. Because these preference measures correspond directly to primitives that shape post-marital household decisions, they allow us to study marital sorting on characteristics that are theoretically first-order but empirically difficult to observe. 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. This pre-marital elicitation, therefore, makes our data an

[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."

ideal setting for analyzing matching and sorting on a rich set of attributes, including preferences over fertility and time allocation.

To study sorting patterns on pre-marital preferences as well as sociodemographic and anthropometric variables, we apply the multidimensional matching framework proposed by Dupuy and Galichon (2014). Given the rich set of variables in our dataset, we do not restrict attention to a single attribute, in contrast to the approach in Choo and Siow (2006) and much of the subsequent literature (Chiappori and Low 2024). Specifically, we examine twelve attributes that are either directly observed or constructed from the data: education, age, income, occupational flexibility, height, weight, drinking habits, smoking habits, marital history, preferences for housework, preferences for childcare, and preferences for children. Crucially, this framework allows us to quantify and disentangle the contributions of multiple attributes and their interactions to observed matching patterns while accounting for potential correlations among them. Ignoring this multidimensional structure and focusing on a single trait may lead to misleading conclusions when that trait is strongly correlated with others.

The estimated affinity matrix, which summarizes whether each male–female attribute combination is complementary or substitutable and thus reflects sorting patterns, reveals several noteworthy findings. First, we document strong positive assortative matching among couples formed on the platform. Strikingly, all twelve attributes we consider, including sociodemographic, anthropometric, and preference measures, exhibit positive assortativeness, a pattern that is not guaranteed ex ante. Because all attributes are recorded prior to matching, these results reflect clean sorting patterns uncontaminated by post-marital coordination. Among the diagonal elements of the affinity matrix governing assortativeness, age exhibits the largest coefficient, consistent with the prior literature such as Chiappori *et al.* (2024). Remarkably, the second-largest coefficient corresponds to preferences for children — exceeding even education, which typically displays one of the strongest assortative patterns. This highlights how our rich dataset uncovers and confirms important dimensions of sorting that are largely invisible in standard data sources.

Second, the off-diagonal elements of the affinity matrix highlight the importance of cross-attribute interactions across genders. Among the sociodemographic attributes (education, age, and income) and anthropometric characteristics (height and weight), all but two interaction coefficients are statistically different from zero. This pattern indicates that possessing a favorable characteristic in one dimension (e.g., higher income) tends to attract a partner with stronger attributes along nearly all other sociodemographic and anthropometric dimensions.

Occupational flexibility, constructed with information on occupation following Goldin (2014), plays a more limited role in sorting than other sociodemographic characteristics. While we observe positive assortative matching along this dimension, its magnitude is relatively small and its interactions with other attributes are largely 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 match formation (Erosa *et al.* 2022, Bang 2021, Calvo *et al.* 2024), it need not be a primary margin of the partner selection stage.

Finally, interactions involving pre-marital preferences for children exhibit distinct patterns. Preferences for children are complements to intentions regarding childcare: individuals willing to assume childcare responsibilities tend to attract partners with a stronger desire for children. In contrast, the interactions between child preferences and sociodemographic or anthropometric attributes are generally indistinguishable from zero. This suggests that, despite the common view that education or income matter for childbearing, a desire for children does not attract partners with higher education or income; nor do highly educated or high-income individuals attract partners with stronger child preferences. These striking patterns are only visible in a multidimensional matching framework with a rich set of attributes.

The model of Dupuy and Galichon (2014) also allows us to assess whether the observed sorting patterns can be summarized by a low-dimensional index through a saliency analysis. The hypothesis that a single index explains the sorting patterns is rejected, although three indices account for almost 90% of the total observable matching surplus. The first index alone explains more than 70% of the joint utility and loads heavily on age, consistent with the well-known tendency for individuals to marry partners of similar age. The second index primarily reflects sociodemographic and anthropometric attributes, with different weights by gender: income and height are most salient for men, whereas weight and height are most salient for women. Preferences for children dominate the third index for both men and women. Its share is 6%, which amounts to more than 20% of the joint utility once we account for the fact that individuals tend to search for partners only within their cohort. Overall, the saliency analysis confirms that preferences for children constitute an important margin of sorting and play a distinct role relative to sociodemographic and anthropometric attributes.

We also examine how marital preferences and sorting patterns evolve over time, taking advantage of our data spanning multiple years. Few existing multidimensional matching studies analyze such dynamics, primarily due to data limitations; researchers typically have either a rich set of attributes or a long time series, but rarely both. Using normalization methods that make estimates comparable across years (Ciscato and Weber 2020), we document several noteworthy trends. First, assortative matching with respect to age, height, weight, and preferences for children remains remarkably stable over the ten-year period. These attributes consistently exhibit strong positive assortativeness, indicating that they have been persistently salient in the matching process. Second, we find a decline in sorting on education alongside an increase in sorting on income. 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 the dating process. Our unique data allow us to address this question because they record not only final match outcomes, but also interactions at each stage of relationship formation, including initial applications for meet-

ings and subsequent decisions to enter exclusive commitments. We therefore examine assortative matching across stages of relationship formation, from Application to Proposal, using a many-to-many matching framework proposed by Fox (2018). The results indicate that assortativeness with respect to age and income is already robust at the Application stage and remains present throughout subsequent stages, whereas assortativeness in marital history and preferences for children is not robustly identified at early stages but becomes evident only at later stages of the pipeline. Other attributes do not display robust assortative patterns at any stage. Overall, this 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. The assumption that households with the same observables may hold heterogeneous fertility preferences, while conceptually natural, is rarely incorporated into theoretical or empirical structural models. It is sometimes implicitly presumed that, largely to avoid added complexity and identification challenges, such heterogeneity is inconsequential for the purpose of estimating average policy effects because aggregation would mask household-level differences. Our theoretical exercise shows that this presumption is incorrect; ignoring preference-based sorting generally leads to overestimated policy effects on fertility and labor supply. Given our empirical finding of significant sorting on preferences for children, analyses that abstract from this form of heterogeneity are likely to yield policy predictions that are 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, Dupuy and Galichon (2014) extend the framework and introduce a flexible, 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

[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).

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 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 casual 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

[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.

[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.

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 occupations 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 data from IBJ, the marriage matching platform in Japan. In Section 3, we present the models of multidimensional matching and the econometric approaches used for estimation. Estimation results are provided in Section 4, while Section 5 discusses their implications for models in household economics. Finally, Section 6 concludes.

2 Data

This section describes the IBJ data and institutional environment and presents summary statistics. 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 reports summary statistics for matched couples in 2024 used in the main estimation.

[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).

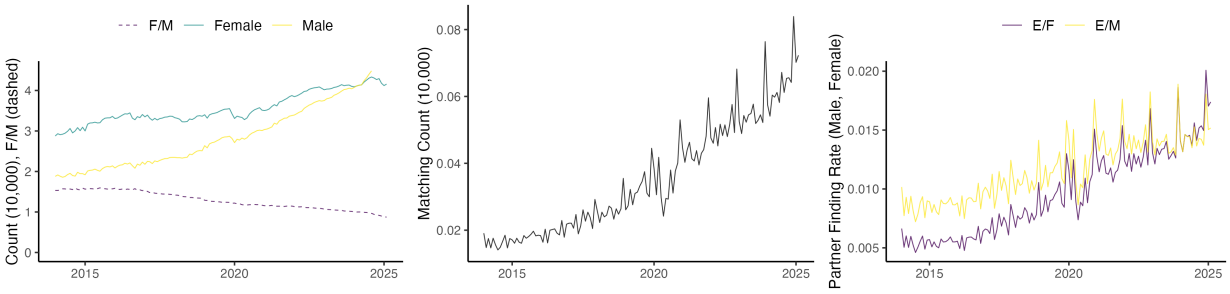
[8] A related literature examines assortative matching by occupation or industry (e.g., Kalmijn 1994). This work typically focuses on occupational titles rather than characteristics of occupations — such as flexibility, schedules, or career dynamics — that are central to intra-household coordination.

Subsection 2.4 documents changes in the characteristics and preferences of matched users between 2015 and 2024.

2.1 A Marriage Agency Platform

IBJ operates as a structured marriage matching platform, designed to facilitate long-term partnerships through a highly intermediated process. Unlike typical dating apps that enable open-ended, user-initiated interaction, IBJ imposes strict entry requirements including documentation checks, health certification, and both upfront and ongoing financial costs. Users are matched through consultant-mediated proposals, and confirmed engagements require bilateral agreement. The platform operates under a one-to-one matching rule and prohibits concurrent engagement. This institutional structure ensures that users are 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 and Market Coverage. The IBJ platform has grown significantly over time, both in user participation and in the volume of matches. As shown in Figure 1, the number of active users increased steadily between 2014 and 2025, with particularly sharp growth on the male side after 2020. This gender-specific expansion led to a decline in market tightness (the female-to-male ratio), altering the matching environment. Over the same period, the number of engagements rose markedly, especially after 2020. In 2024, IBJ facilitated over 10,000 engagements, accounting for 3.3% of all marriages in Japan.[10] This level of market coverage—particularly for a platform with high verification and intentionality—offers an unprecedented view into the dynamics 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).

[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.

Verified Matchings In this study, a match is defined as a confirmed engagement formed on the IBJ platform through mutual agreement. Because the platform enforces strict matching rules—including the prohibition of concurrent engagements and the presence of consultant-mediated confirmation—the observed engagements are highly credible indicators of successful match formation. Furthermore, engagements are time-stamped and linked to full behavioral histories, allowing us to trace exactly when and how matches are formed, that is, dating processes explained in Section 2.2. This institutional design minimizes false positives and makes the definition of matching both operationally clear and empirically reliable.

Verified Variables The data collected by IBJ include highly verified demographic and behavioral variables. Key covariates such as age, education, income, health information, and marital history are cross-checked with government-issued documents, tax records, and certified medical examinations. Moreover, user behavior is tracked at high frequency and with timestamps, capturing searches, proposals, messages, and mutual agreement. This degree of data integrity stands in contrast to typical self-reported datasets used in research with online dating data (Hitsch *et al.* 2010a) and survey data (Dupuy and Galichon 2014, Chiappori *et al.* 2024) and allows for rigorous analysis of matching outcomes and behavioral determinants.

The data also contain information on individuals' occupation categories. Because employer information is observed as part of the income verification process, the recorded occupations are highly reliable. We construct an occupational flexibility index following Goldin (2014), who maps occupational titles to characteristics capturing the extent to which jobs reward long and inflexible hours. Occupational characteristics are drawn from the Japanese Occupational Information Network (O-NET), a comprehensive occupational information database developed by the Ministry of Health, Labour and Welfare, Japan, modeled on the U.S. O*NET system. We obtain occupation-level measures corresponding to Goldin's five job characteristics: time pressure, contact with others, interpersonal relationships, structured work, and freedom to make decisions. Each characteristic is standardized to have mean zero and unit variance at the occupation level. For each IBJ occupation category, we aggregate the standardized characteristics across the corresponding O-NET occupations using simple averages. The final flexibility index is defined as the average of the five standardized components, with signs normalized so that higher values indicate greater flexibility. These characteristics are then aggregated into a composite flexibility measure at the individual level. Although occupational flexibility is not a standard individual attribute in the marriage market literature, it captures constraints on time use and career dynamics that are central to intra-household allocation, and therefore plausibly relevant for partner selection.

2.2 IBJ Users' Dating Process and Stage

Table 1 summarizes the sequential structure of partner formation on the IBJ platform, highlighting the distinction between non-exclusive exploration and exclusive commitment. The process starts at the Application stage, where users search and view profiles and may initiate contact by submitting

an *omiai* request to a potential partner. Importantly, initiation is not gender-specific: both men and women can send applications. A submitted request leads to the Omiai Meeting stage only if it is accepted by the recipient, after which the pair meets either in person or online and independently decides whether to continue.

Conditional on mutual approval after the initial meeting, the pair enters the Pre-relationship stage, which consists of a sequence of non-exclusive dates. At this stage, users may simultaneously interact with multiple partners, repeatedly choosing whether to proceed to another date or discontinue with a given match. The platform thus allows broad exploration and screening before any exclusivity is imposed. If both parties subsequently agree to deepen the relationship, they transition to the Serious relationship stage, where interactions become exclusive. This stage involves repeated committed dates with the same partner, during which either party can still choose to exit. The final outcome of the process is engagement at the Proposal stage, i.e., matching, which occurs only when both users mutually confirm their intention to marry. Overall, the platform is designed to move users gradually from open, non-exclusive search toward exclusive commitment through a series of mutually agreed-upon 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 summary statistics of stage-specific activity counts per user in 2024, separately by gender, for users who matched at least once at the Application stage. Because the sample is conditioned on initial Application activity, counts at subsequent stages—including Pre-relationship, Serious relationship, and Proposal—may be zero for users who exit earlier in the process. The statistics aggregate actions across proposer and receiver roles and thus capture total engagement at each stage. The table reveals a sharply funnel-shaped dating process: Application activity is extremely intensive and highly dispersed for both men and women, with mean counts exceeding 100 and very large standard deviations, whereas participation declines dramatically at later stages.

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

Gender		N	Mean	SD	Min	Max
Male	Application	56916	119.93	210.58	1.00	15788.00
	Pre-relation	56916	2.28	3.25	0.00	50.00
	Serious-relation	56916	0.21	0.43	0.00	3.00
	Proposal	56916	0.10	0.31	0.00	2.00
Female	Application	60065	113.64	134.29	1.00	2376.00
	Pre-relation	60065	2.16	2.92	0.00	39.00
	Serious-relation	60065	0.20	0.42	0.00	3.00
	Proposal	60065	0.10	0.30	0.00	2.00

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.

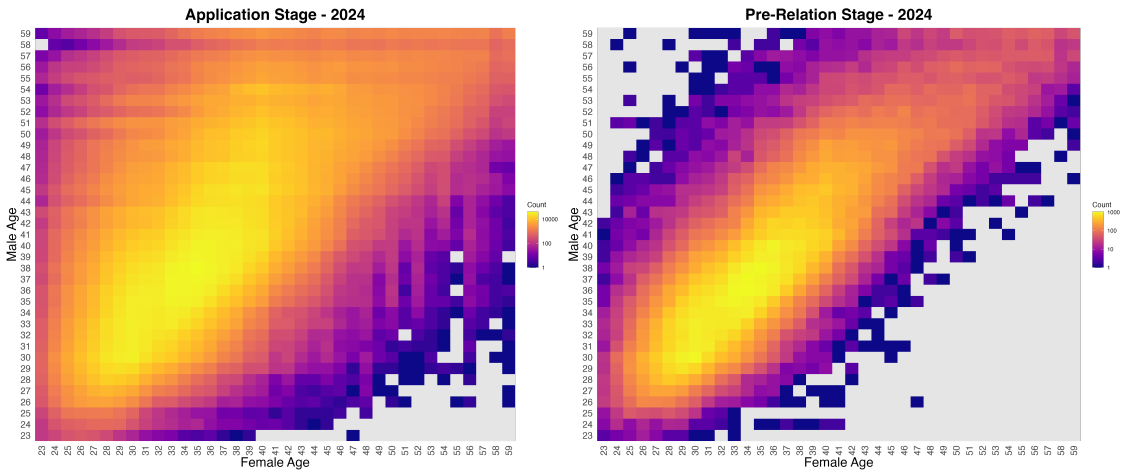
Average activity falls to just above two at the Pre-relationship stage, to around 0.2 at the Serious relationship stage, and to approximately 0.1 at the Proposal stage, reflecting substantial attrition as interactions progress toward exclusivity and final commitment. This steep decline underscores that only a small fraction of early interactions survive to later stages, implying that assortative matching observed at the Proposal stage may arise not only from preferences at the point of final agreement but also from cumulative selection operating across stages.

Figure 2 provides a complementary visualization of matching patterns by age across stages in 2024. When focusing on age as a single dimension, the heatmaps reveal a clear diagonal concentration even at the Application stage, suggesting that age-assortative interactions are already present at the onset of search. However, because this representation conditions only on age, the apparent assortativeness may partly reflect selection driven by other correlated attributes—such as education, income, or family-related preferences—that are jointly considered when users initiate and continue interactions. As a result, one-dimensional age-based patterns cannot distinguish whether assortative matching truly originates at early stages or is induced by multidimensional sorting along 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.

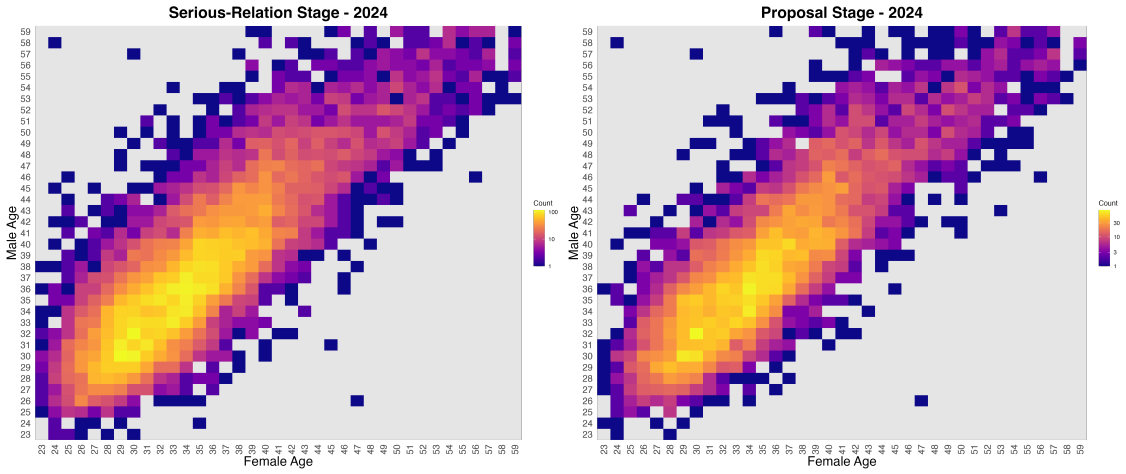
2.3 Summary Statistics of Matched Users in 2024

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 (39.86 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 of 792.91 thousand yen compared to 563.62 thousand yen for women. These differences reflect well-established gender



(a) Application

(b) Pre-relationship



(c) Serious relationship

(d) Proposal

Figure 2: 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.

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, 8.05 for men) and income (200.48 for women, 347.35 for men). 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, women in the sample tend to have higher educational attainment: 6.7% of women hold graduate degrees compared to 1.8% of men, and 62.0% of women have at least a university degree versus 56.0% of men. Drinking and smoking habits differ by gender: 20.5% of men are regular drinkers compared to 15.5% of women, and 3.3% of men regularly smoke versus only 0.4% of women. Meanwhile, the majority of both genders report never having been married

before (91.2% of women, 86.4% of men). Regarding household preferences, women are more likely to express a desire to share or actively engage in housework (88.7% combined for "Share Equally" and "Do It Myself"), while men are slightly more conservative in these views. Preferences for child-rearing and desire for children are also broadly aligned, although women are marginally more likely to express a strong desire for children (21.8% vs. 16.6%).

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

Figure 3 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 remarkably 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 share earning in the 3 million JPY range declined sharply from about 45% in 2015 to 25% in 2024, while the 4 million JPY group remained relatively stable at around 25%. Most notably, the proportion of women earning 5 million JPY or more rose significantly from roughly 30% to 50% over the same period. This substantial shift suggests that women's economic attractiveness—traditionally less emphasized in the marriage market—has become increasingly important. Educational attainment also improved modestly, particularly among women, with a gradual rise in the share holding undergraduate and graduate degrees.

Figure 4 illustrates the evolution of lifestyle habits, marital history, and family preferences among married individuals from 2015 to 2024. Panels (a) and (b) show that while most individuals abstain from smoking and drinking, gender gaps persist: women are consistently less likely to drink 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, particularly among women, indicating a slight softening of parenthood norms. Panels (e) and (f), which appear from 2020 onward, highlight significant gender asymmetries in stated preferences for the division of childcare and housework. While men are more likely to prefer leaving these responsibilities to their partner, 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 little sign of convergence.

Figure 5 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.

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

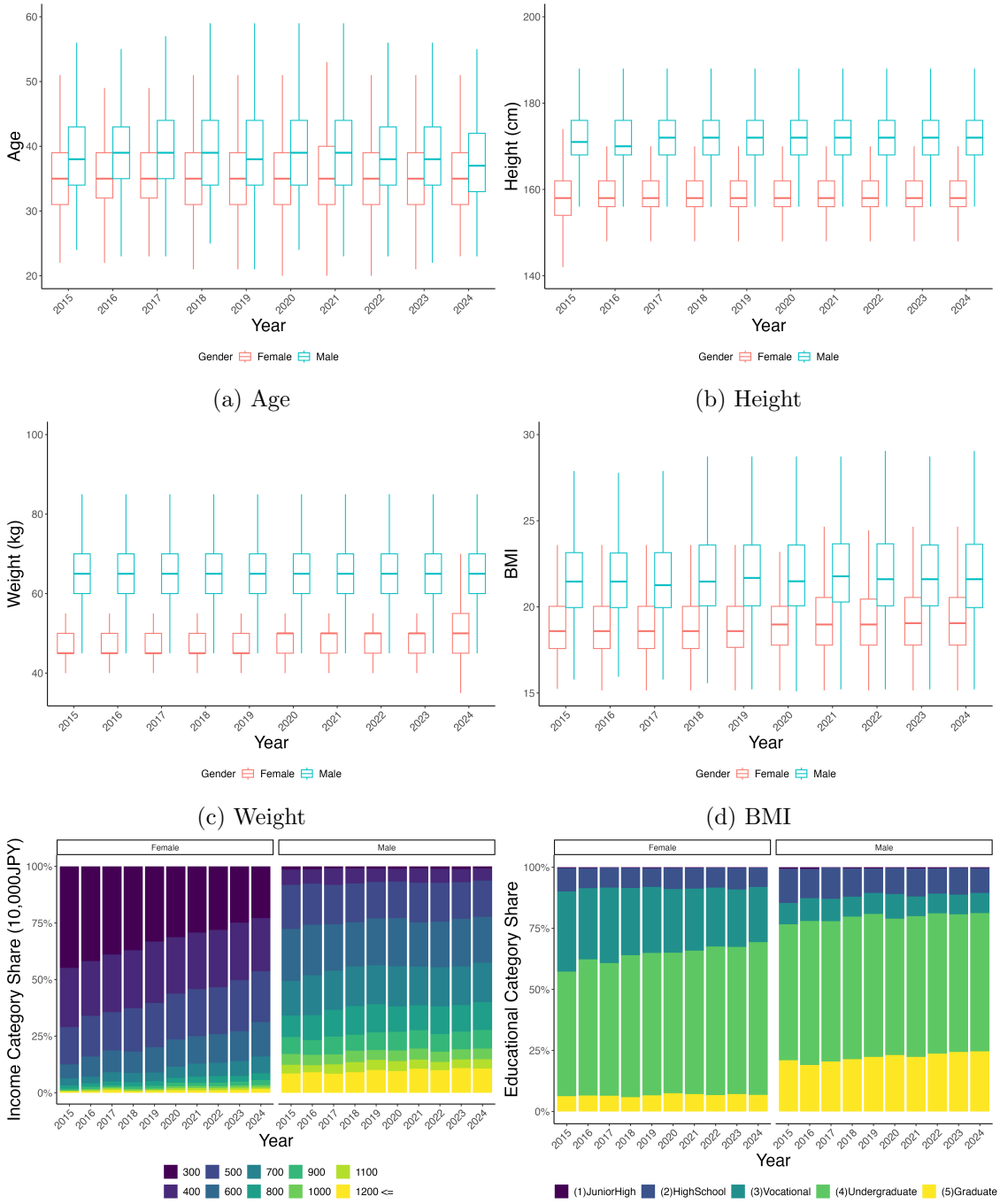
(a) Continuous

Gender		N	mean	median	sd	min	max
female	Age	7562	36.01	35.00	7.15	23.00	75.00
	Income	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	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: Occupational Flexibility follows Goldin (2014).



(a) Age

(b) Height

(c) Weight

(d) BMI

(e) Income Category

(f) Education

Figure 3: 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 4: 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.

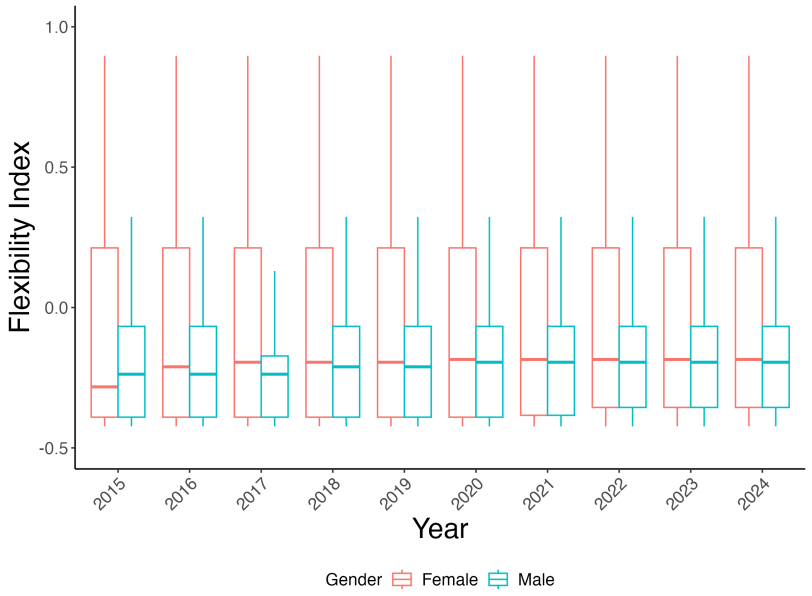


Figure 5: Distribution of Occupational Flexibility in Married Couples

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.

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 on one parameter as well as assumptions for comparisons across markets, which limit the interpretability of individual coefficients, it accommodates many-to-many matching and is therefore appropriate for analyzing dating stages in which agents may simultaneously interact with multiple potential partners.

3.1 TU Multidimensional Continuous-Type Quadratic Matching Model

We consider a frictionless transferable utility model of the marriage market, in which each man and woman is described by a vector of 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 $\pi(x, y)$ that represents the likelihood of a man of type x and a woman of type y forming a match. Upon matching, partners receive deterministic utility components $U(x, y)$ and $V(x, y)$, respectively, as well as individual-specific stochastic utility shocks.

Following the approach by Dupuy and Galichon (2014), we assume that each agent draws an infinite sequence of potential partners characterized by both observable traits and idiosyncratic preference shocks. For example, a man evaluates matches over a countable set of women $\{(y^k, \varepsilon^k)\}_{k=1}^{\infty}$, where each ε^k is drawn independently from a type I extreme value distribution. This setup yields a continuous logit formulation in which the man's utility from matching with y^k is given by $U(x, y^k) + \frac{\sigma}{2}\varepsilon^k$, where σ indexes the relative importance of idiosyncratic versus systematic preferences. An analogous 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 the total systematic surplus of a match between x and y, and $a(x)$, $b(y)$ are type-specific adjustment terms ensuring that the total number of matches does not exceed the supply of each type. The shares of surplus allocated to each side are then given by:

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

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 affinity matrix A, of dimension $O \times O$, summarizes how individual traits interact in the matching process and is the central object of interest. Its elements encode both the magnitude and the sign of interactions across characteristics: a positive coefficient a_{ij} indicates complementarity between traits x_i and y_j, whereas a negative value reflects substitutability.

Estimation proceeds by exploiting the structure of the equilibrium matching problem. As shown by Dupuy and Galichon (2014), $B = A/\sigma$ can be recovered as the solution to the convex optimization problem

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

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

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

and expectations indexed by $\hat{\pi}$ are computed using the empirical joint distribution of observed matches in the data.

The optimality conditions associated with this problem yield a set of moment-matching re-

strictions. Intuitively, the estimated matching model must reproduce the joint distribution of characteristics observed in actual matches. In particular, the equilibrium matching distribution implied by the model equates the 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 therefore amounts to selecting B so that the model-generated pattern of assortative matching aligns with its empirical counterpart.

Saliency analysis. An important implication of the quadratic surplus specification is that it admits a low-dimensional representation of assortative forces. In particular, the affinity matrix A can be factorized using a singular value decomposition (SVD), which provides a transparent way to characterize 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 containing positive singular values ordered from largest to smallest, and U and V collect the associated loading vectors. Each singular value reflects the relative importance of a distinct dimension of assortative matching, while the corresponding loading vectors describe how observable characteristics load onto that dimension on each side of the market.

This decomposition allows the surplus function to be re-expressed as a sum of independent components. Defining transformed characteristics $\tilde{x} = Ux$ and $\tilde{y} = Vy$, the surplus can be written as

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

where each term captures the contribution of a separate dimension of assortativeness. In this representation, assortative matching operates through a set of orthogonal indices, with higher singular values corresponding to dimensions that play a more prominent role in shaping observed matching patterns.

In the empirical analysis, we apply this decomposition to the estimated affinity matrix $\hat{A}$ in order to recover estimates of U, V, and Λ. This approach enables us to assess both the relative importance of different dimensions of assortative matching and the specific combinations of observable traits that define them. Sampling uncertainty for these objects can be quantified using bootstrap procedures.

An important remaining issue is the dimensionality of assortative matching. Following Dupuy and Galichon (2014), we conduct rank-based tests on the estimated affinity matrix. The null hypothesis restricts $rank(A) = k$; rejection implies that assortative matching operates along more than k economically relevant dimensions.

Identification with multiple years. Since the data span the period from 2015 to 2024, one could estimate the affinity matrix separately for each year and examine whether, and how, sorting forces have evolved over time. However, because the affinity matrix A is identified only up to scale, i.e., only $B = A/\sigma$ is identified, additional restrictions are required to enable meaningful comparisons across years.

To facilitate such comparisons, we follow Ciscato and Weber (2020) and impose a normalization that sets the Frobenius norm of the affinity matrix A^t equal to one for every year t, that is, $\|A^t\| = 1$. [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 can thus recover A^t, which is directly comparable across years and allows us to study trends in sorting patterns over time. At the same time, the time series of σ^t provides information on changes in the relative importance of unobserved heterogeneity in the matching process.

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 shown in Section 2.2 and defines stage-specific assortativeness measures computed from 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 of the pipeline, agents form potentially multiple relationships, and equilibrium outcomes are characterized as competitive allocations over portfolios of trades, proposed by Azevedo and Hatfield (2018), rather than single matches. Preferences are specified over observable characteristics only, with the deterministic component of surplus parameterized linearly in a vector of stage-specific coefficients. By restricting attention to bilinear interactions between male and female continuous attributes, the estimated parameters can be collected into a stage-specific affinity matrix, whose diagonal elements capture assortative matching and whose off-diagonal elements represent cross-attribute complementarities. Identification relies on the rank-order property implied by exchangeable unobserved heterogeneity, and estimation proceeds via the matching maximum score estimator, which delivers set-consistent estimates of the affinity matrix up to scale within each stage.

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

Although both this framework and the multidimensional matching approach of Dupuy and Galichon (2014) employ bilinear surplus specifications, the two models differ fundamentally in their equilibrium concepts and identifying variation. Dupuy and Galichon study one-to-one matching in a continuous logit environment, where an entropic regularization yields a unique matching density

[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 that encodes the observable characteristics of the two participants and (optionally) additional observable contract/stage features. See Fox (2018) for the trading-network equilibrium and matching maximum score estimation approach.

and allows the affinity matrix to be identified on a cardinal scale. In contrast, the Fox (2018) framework does not impose a parametric distribution on unobserved heterogeneity and identifies preferences only up to scale through equilibrium stability inequalities. As a result, the affinity matrices estimated here are not comparable across stages or over time in levels, and are instead interpreted in terms of sign robustness and within-stage relative importance. Accordingly, while the Dupuy–Galichon approach is well suited for analyzing cross-sectional levels and long-run trends at the Proposal stage, the Fox framework is used to trace when assortative patterns become robustly identified along the matching pipeline, rather than to measure changes in their magnitude.

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 4 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 (3.63), 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 female education–male income (0.11) exceeds that for male education–female income (0.07). Interactions involving physical at-

tributes 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, a 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, all but one interaction coefficient 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. 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 chil-

[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).

dren are negative (−0.05 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 sociodemographic or anthropometric attributes are generally close to zero. This implies that fertility preferences constitute a distinct margin of sorting that operates largely independently of education, income, and 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 5 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 (0.25 for men, 0.22 for women), income (0.65 and 0.39), 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 4: 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. Standard errors, reported in parentheses, are obtained from 2,000 bootstrap replications. Estimates in bold are statistically significant at the 5% level.

Table 5: 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 $\text{diag}(\Lambda)$, obtained from the singular value decomposition of the affinity matrix $A = U'\Lambda V$. The final row reports the elements of $\text{diag}(\Lambda)$, 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 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).

Table 6 reports the rescaled diagonal elements of the affinity matrix at the Proposal stage from 2015 to 2024, allowing for a direct comparison of assortative matching patterns over time.[14] 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 0.92 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.

[14] The contribution of unobserved heterogeneity increases during the early years of the sample period but returns to its initial level by 2024; see Table 7.

Table 6: 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 element 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.

Table 7: 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.

4.3 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 8 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.

Table 8: 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. The full interaction model is shown in Appendix B.2.

5 Discussion: Implications for Household Economics

A distinctive feature of our data is that it records 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 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. The optimal fertility choice is

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

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. [15]

The economic intuition can be illustrated by an extreme case in which preferences for children 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 [16] 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

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

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

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

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.

[16] 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.

2017, Yamaguchi 2019, Kim *et al.* 2024, Jakobsen *et al.* 2024). [17] 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.[18]

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 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

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

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

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.

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A Appendix: Data

A.1 IBJ Data Advantage Compared with Related Literature

Table 9 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 9: 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 10 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 substantially less educated: only 51.4% of unmatched men and 64.5% of unmatched women have at least a university degree, compared to 56.0% and 62.0%, respectively, among matched individuals. Additionally, unmatched men are more likely to smoke regularly (3.9% vs. 3.3%) and drink regularly (27.5% vs. 20.5%), suggesting potentially less health-conscious lifestyles. Differences in household attitudes are also present: unmatched women are somewhat less inclined to actively participate in housework ("Do It Myself": 35.7% unmatched vs. 38.2% matched), and unmatched men are less likely to express a strong desire for children (16.0% unmatched vs. 16.6% matched). These patterns indicate that both observable

human capital and alignment in household preferences may play a role in selection into match.

Table 10: 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	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	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 4.3

Let $t \in \mathcal{T} = \{\text{Application}, \text{Pre-relationship}, \text{Serious relationship}, \text{Proposal}\}$ index stages of the IBJ pipeline.[19] 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.[20] 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,

[19] 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.

[20] 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.[21]

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 $X_t(\omega)^\top \theta_t = X\left(b\left(\omega\right), \Phi_{b(\omega)}, \Psi_{b(\omega)}\right)^\top \theta_t + X\left(s\left(\omega\right), \Phi_{s(\omega)}, \Psi_{s(\omega)}\right)^\top \theta_t$ is a vector of observable trade features derived from the matching induced by $\omega = (m, w)$. 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

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

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

$$x_m^\top A_t y_w.$$

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

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.

B.2 A Many-to-Many TU Matching Model: Full interaction

Tables 11 and 12 compare the baseline specification in Table 8 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—most notably robust positive assortative matching on age, income, marital history, and preferences for children—remain qualitatively unchanged across specifications. The stability of these diagonal estimates suggests that the core assortative patterns identified in the baseline model are not driven by omitted cross-attribute interactions. 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 11: 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 detail in the main text.

Table 12: 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 detail in the main text.

B.3 Assortativeness in TU One-dimensional Discrete-Type Model (Choo and Siow 2006) in 2024

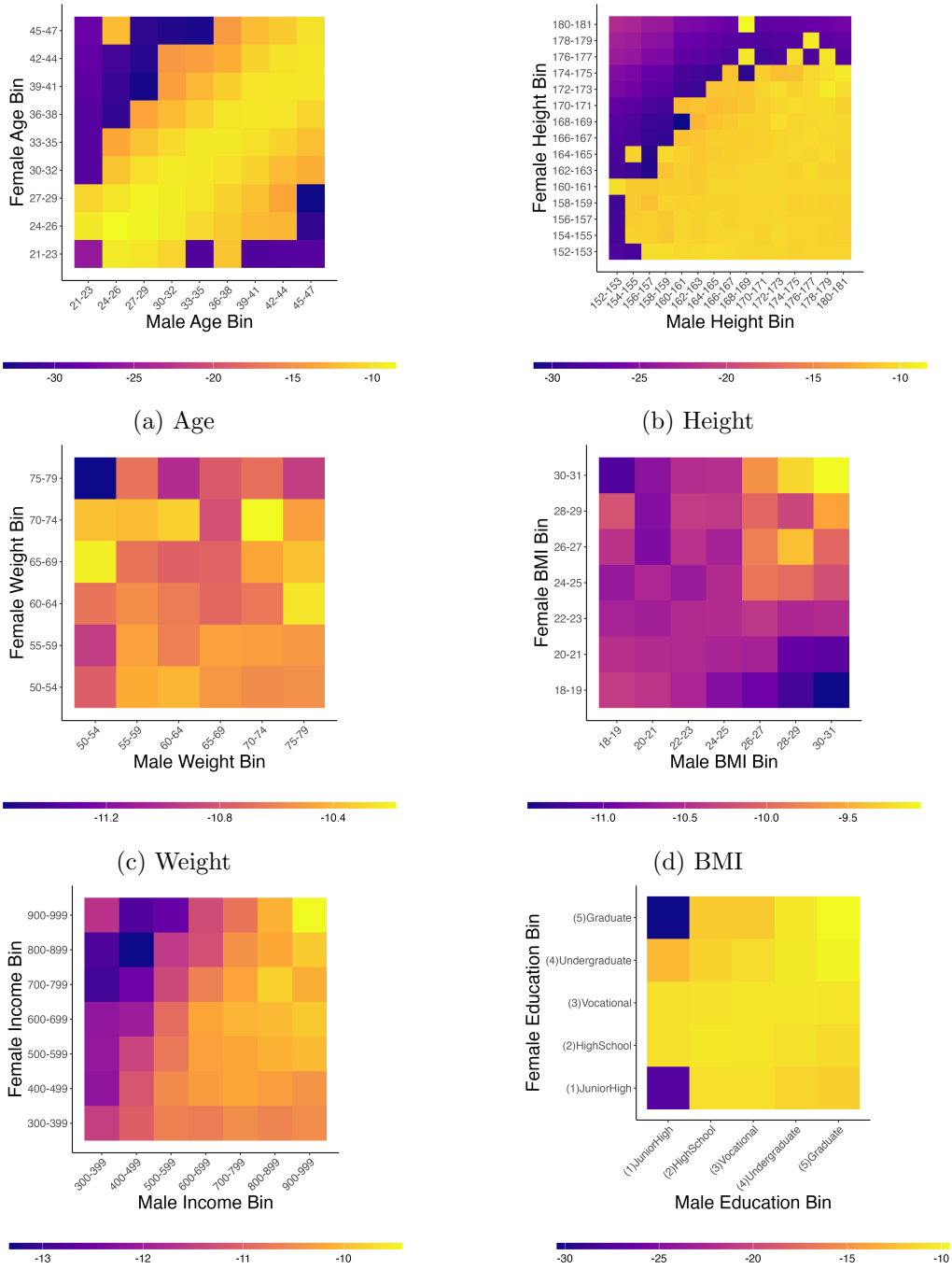
To highlight the dataset's granularity and novelty, we first apply the well-known framework of Choo and Siow (2006) to quantify assortative matching patterns and compare the contribution of each observed characteristic to match surplus.[22]

Anthropometric physical attractiveness Figure 6 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 maximized along the diagonal, with younger women most strongly matched to slightly older men. The highest surplus values are concentrated between women aged 26–35 and men aged 31–40. Surplus declines sharply as age differences increase, particularly in matches involving older women and much younger men, reinforcing the prevalence of age-homogamy and modest male-age advantage in the matching process. These results echo common patterns in marriage timing and are consistent with age-related preferences and fertility considerations.

Panels (b) through (d) in Figure 6 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 more scattered and asymmetric patterns, with somewhat higher surplus among average-weight men and lighter women. Panel (d) indicates that BMI-based sorting captures both height and weight effects, showing peak surplus in the mid-range of BMI values 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 preferences.

Sociodemographic attractiveness Panels (e) and (f) in Figure 6 depict sorting patterns on income and education, capturing sociodemographic dimensions of match surplus. The income plot reveals surplus increasing in male income, but less strongly so in female income—a pattern consistent with gender-asymmetric expectations around economic roles. The education panel shows strong positive assortative matching, especially between individuals with college and graduate-level degrees. Notably, matches involving lower education levels (e.g., junior high school) are associated with low or negative surplus, especially when asymmetrically paired with highly educated partners. These results highlight the salience of both economic capacity and educational alignment in shaping match gains in the marriage market.

[22] Following Choo and Siow (2006), we estimate the systematic surplus $\hat{\Phi}_{ij}$ using the relation $\mu_{ij} = \mu_{i0}\mu_{0j}\exp(\Phi_{ij})$, 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 $\hat{\Phi}_{ij} = \log\mu_{ij} - \log\mu_{i0} - \log\mu_{0j}$. 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 6: Systematic Surplus in Anthropometric and Sociodemographic Attractiveness

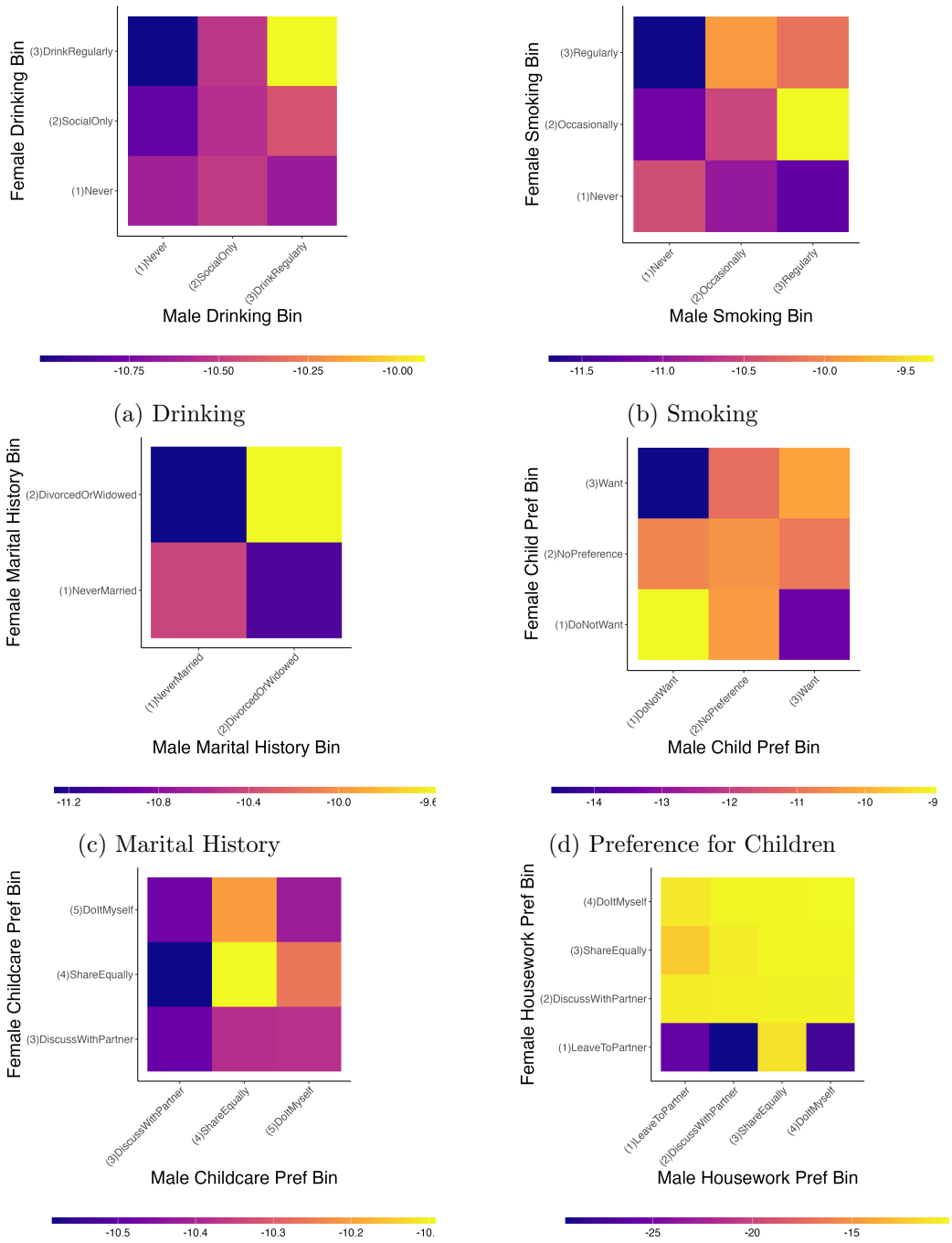
Note: Anthropometric physical attractiveness is captured by age, height, weight, and BMI. Sociodemographic attractiveness is captured by income and education. See Chiappori *et al.* (2012) and Dupuy and Galichon (2014) for discussion of the use of these characteristics.

Health and Lifestyle Preferences Panels (a) and (b) in Figure 7 present surplus estimates by drinking and smoking habits. These lifestyle traits exhibit modest assortative matching pat-

terns. For both drinking and smoking, surplus is highest when partners share similar preferences—particularly when both abstain or both engage at moderate levels. Notably, matches between regular drinkers and non-drinkers (or smokers and non-smokers) tend to generate lower surplus, suggesting disutility from mismatched lifestyle choices. While these factors do not dominate match surplus overall, they reflect nontrivial complementarities in daily routines and social behavior that may influence long-term compatibility.

Marital History Panel (c) in Figure 7 focuses on marital history, distinguishing between never-married individuals and those who are divorced or widowed. The highest surplus is generated when both partners have never been married, while matches involving one previously married individual and one never-married individual yield lower surplus. This asymmetry suggests that shared life course trajectories—especially regarding first-time marriage—may play an important role in perceived compatibility. It also reflects the possibility that previously married individuals are evaluated differently in the matching process, perhaps due to perceived experience, readiness, or stigma.

Preferences over Family Formation Panels (d) through (f) in Figure 7 explore preferences related to family formation, including desire for children, childcare attitudes, and housework division. All three attributes display strong assortative matching: surplus is highest when both partners express similar preferences. For example, couples where both strongly desire children or agree on equal division of childcare and housework enjoy higher joint surplus. Mismatches, particularly between partners who want children and those who do not, or between individuals with conflicting views on domestic labor, are associated with lower surplus. These findings underscore the importance of alignment in family-related values at the matching stage, suggesting that such preferences are not merely downstream determinants of marital outcomes, but also core dimensions of the matching process itself.



(a) Drinking

(b) Smoking

(c) Marital History

(d) Preference for Children

(e) Childcare

(f) Housework

Figure 7: 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.