Matching on Height in India

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Abstract

In India, height is greatly valued in the marriage market, and the child stunting rate remains strikingly high. In this paper, I juxtapose these two seemingly unrelated facts and investigate the role of parents' marital sorting and matching in determining children's height. First, I develop a two-sided matching model of the Indian marriage market to structurally estimate preferences for height. I do so while considering other critical drivers of marital sorting and matching, such as education and family wealth. I find evidence of significant positive assortative matching on height across religion-caste groups. Next, I study the change in complementarity in height over time, finding a mild increase on average but substantial heterogeneity by caste and religion. Finally, using the model estimates, I simulate parents' counterfactual joint height distribution under several hypothetical scenarios. Based on insights from the medical literature, I compute children's potential height distribution (and hence their risk of being stunted) given the counterfactual distribution of matches. I find marital matching to have a limited impact on children's average height, but a significant one on the level of inequality in children's height. Specifically, my analysis indicates that complementarity in height in the marriage market can increase the standard deviation of the distribution of potential height by up to 3% and the prevalence of stunting by up to 4 percentage points.

Keywords: Marriage, Height, Stunting, India, Transferable Utility.

JEL codes: J11, J12, J16

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All errors are my own.

1 Introduction

Indian children face a strikingly high risk of stunting, with 31% of children between the ages of 0-5 being too short for their age (UNICEF, World Bank Group, and WHO, 2021).[1] India also has one of the world's shortest adult population. According to the latest global height rankings, Indian men and women rank 178 and 180 out of 198 countries, respectively.[2] Contrary to many other developing countries, over the last century, the height of Indians has increased marginally. On average, Indian men and women have grown by just three and five centimeters, respectively (NCD Risk Factor Collaboration, 2016).[3]

Previous work has investigated the role of malnutrition, the disease environment, son preference and women's bargaining power as the main determinants of the low height-for-age of Indian children (Deaton, 2007; Coffey, Deaton, Drèze, Spears, and Tarozzi, 2013a; Coffey, Khera, and Spears, 2013b; Jayachandran and Pande, 2017; Coffey and Spears, 2017; Calvi, Lewbel, and Tommasi, 2021). Since height is a highly heritable trait, parental height also plays a role, and sorting and matching on height in the marriage market in one generation may prove essential to understanding the height distribution in the next.[4] As child height has significant consequences on long-term individual well-being through its association with adult height, cognitive ability, and income (Tanner, Healy, Lockhart, Mackenzie, and Whitehouse, 1956; Case and Paxson, 2008), understanding preferences for height in the marriage market, how they have evolved over time, and how they may affect the height distribution of the next generation is of primary importance.[5]

Common wisdom is that height is greatly valued in the marriage market in India.[6] In this paper, I study this fact rigorously and estimate preferences for height in the Indian marriage market using a two-sided matching model with transferable utility. Based on the model estimates and insights from the medical literature, I analyze how parents' marital matching on height impact children's height distribution and risk of stunting. My analysis indicates that complementarities in height in the marriage market can increase the standard deviation of the distribution of children's height by up to 3% and the prevalence of stunting by up to 4 percentage points.

I start by providing descriptive evidence of the relationship between husband's and wife's attributes in the spirit of Oreffice and Quintana-Domeque (2010) using data from the second wave of the Indian Human Development Survey (IHDS). I find strong positive associations between men's and women's height, education, and parental education, indicating positive assortative matching along these attributes. Next, I quantify the impact of parental height on children's height. Conditional on household-level determinants and demographic characteristics, I find that a child with both parents with an above-median height has a

[1]A child is defined as stunted if their height-for-age is two standard deviations or more below the world reference population median for a given gender and age.

[2]The average height of Indian men and women is 166 and 155 centimeters, respectively. Source: https://worldpopulationreview.com/country-rankings/average-height-by-country

[3]In contrast, the height of Chinese and Brazilian adults on average has increased by more than ten centimeters.

[4]Evidence from medical literature suggesting that up to 80% of the variation in height can be explained by genetics (Stulp and Barrett, 2016).

[5]There is a vast literature from evolutionary biology and sociology studying the importance of anthropometric features in the marriage market (see Courtiol, Raymond, Godelle, and Ferdy (2010) for a review of the literature from evolutionary biology and Stulp, Simons, Grasman, and Pollet (2017) for a meta-analysis, summarizing the literature from sociology). A growing number of research articles in economics have also analyzed marital sorting and matching on physical attributes, such as height, weight, and body mass index. Most of these works, however, have focused on developed countries (Oreffice and Quintana-Domeque, 2010; Chiappori, Oreffice, and Quintana-Domeque, 2012, 2016). A notable exception is a very recent paper by Chiappori, Ong, Yang, and Zhang (2021) studying marital preferences for height in China.

[6]A common practice in India is to place matrimonial advertisements in newspapers to look for a spouse. Height is mentioned in the ad by over 90% of adults (Banerjee, Duflo, Ghatak, and Lafortune, 2013). Another common practice in India is to look for a spouse on matrimonial websites. On most of these websites, individuals looking for a spouse list their height (see the following link for an example: https://www.jeevansathi.com/matrimonials/hindu-matrimonial). From the recent Netflix show, Indian Matchmaking, one of Mumbai's (a large metropolitan city in India) top matchmakers says the following about the Indian marriage market: "In India, we have to see the caste, we have to see the height, we have to see the age."

0.7 standard deviations larger height-for-age than a child with both parents with a below-median height. Similarly, a child with both parents with an above-median height has a 16 percentage point lower probability of stunting than a child with both parents with a below-median height.[7] This analysis provides preliminary evidence of some of the relevant dimensions of marital matching in India and how matching on height can impact children's height.

To understand the role of preferences for height in the Indian marriage market, I estimate a structural static frictionless two-sided transferable utility model of the marriage market using the framework of Dupuy and Galichon (2014). In this framework, every man and woman in the marriage market is characterized by a feature vector consisting of height, education, father's education, mother's education, and age. The critical component of the model is the "affinity matrix", which measures the intensity of complementarity/substitutability across features.[8] Since inter-caste or inter-faith marriages are extremely rare in India (Banerjee et al., 2013; Borker, Eeckhout, Luke, Minz, Munshi, and Swaminathan, 2017), I model each religion-caste group, Scheduled Caste, Scheduled Tribe, Other Backward Caste, Upper Caste, and Muslims as a separate marriage market.[9] For each market, I estimate the complementarity in height, education, parental education, and age, as well as the cross-complementarities between them.

The affinity matrix estimates indicate strong positive assortative matching on height, with taller men and women finding each other mutually attractive in the marriage market in India. For the majority of religion-caste groups, I find evidence of cross-complementarity in men's education and women's height, indicating that more educated men and taller women find each other mutually attractive in the marriage market. Results also indicate cross-complementarity in men's height and women's father's education, suggesting that taller men and women from wealthier families find each other mutually attractive. Similarly, the results show significant positive assortative matching between more educated men and women from more affluent families. Lastly, I also find evidence of cross-complementarity between women's education and men's mother's education.

Marital sorting and matching patterns have been shown to have important consequences for the intergenerational transmission of inequality (Greenwood, Guner, Kocharkov, and Santos, 2014; Chiappori, Salanié, and Weiss, 2017; Ciscato and Weber, 2020). There is a growing strand of literature studying the changes in marital sorting and matching patterns over time in developing countries, focusing on changes in matching on education (Smits and Park, 2009; Hoehn-Velasco and Penglase, 2021). I contribute to this literature by analyzing changes in marital matching on height. In particular, I estimate the affinity matrix separately for an old and a young cohort and compute the change in complementarity in height. The results indicate significant heterogeneity across religion-caste groups.[10] I find the degree of assorta-

[7]The medical literature documents a strong association between parental height, in particular maternal height and the offspring's stunting hazard, across the developing world (Özaltin, Hill, and Subramanian, 2010).

[8]A primitive of the transferable utility model is the joint marital surplus. Intuitively, an equilibrium matching distribution is determined by maximizing the sum of marital surplus over all possible matches. The second derivative of the joint marital surplus concerning a man and a woman's characteristics is the complementary/substitutability between the two features. For example, the complementary/substitutability in height is the second derivative of the joint marital surplus with respect to the height of men and women. See Section 4 for details.

[9]According to the IHDS, 95% of the respondents marry someone within their own caste.

Articles 341 and 342 of the Indian constitution define the term Scheduled Caste and Scheduled Tribe precisely, respectively. Individuals belonging to these castes suffer from extreme forms of social, educational, and economic backwardness with much lower living standards than the rest of the population (Gang, Sen, and Yun, 2008). The Other Backward Caste community consists of individuals who are better off than Scheduled Caste and Scheduled Tribe members but less well-to-do than Upper Caste members. According to the 2011 census, 80% of Indians are Hindus, 14% are Muslims, and Scheduled Caste and Scheduled Tribes comprise 16.6% and 8.6%, respectively, of India's population. The Census does not provide numbers for the Other Backward Caste. However, according to the 2015 National Family Health Survey, 44% of individuals belong to the Other Backward Caste community, making it the largest caste group in India.

Ideally, we would like to model district-religion-caste-specific marriage markets, given that most marriages in India are within a given district. The average travel time between the marital and natal family is 3-4 hours (Beauchamp, Calvi, and Fulford, 2017; Fulford, 2013); however, due to the sample size, this is not feasible. As a result, I consider religion-caste-specific marriage markets instead of district-religion-caste-specific marriage markets.

[10]In particular, I define two non-overlapping cohorts: the old cohort consists of men born between 1950-1960 and married to women born between

tiveness on height to have increased over time for couples belonging to the Scheduled Tribe, Muslim, and the Other Backward Caste group. In contrast, I find no change for couples belonging to the Upper Caste or the Scheduled Caste.

Using the model estimates and insights from the medical literature, I simulate several counterfactual experiments. In the first experiment, I evaluate children's potential height distribution under various hypothetical marriage market preferences.[11] The analysis involves two steps. In the first step, I compute the joint distribution of men's and women's height under the hypothetical scenario of no complementarity in height in the marriage market. In the second step, I simulate children's counterfactual potential height distribution using the computed hypothetical joint distribution of height. Results from the simulation indicate that, although children's average potential height does not change, there are substantial effects on the potential height distribution. In the absence of complementarity in height, we see a decrease in the prevalence of children with short stature and a reduction in the prevalence of children with tall stature. As a consequence, the standard deviation of the potential height distribution decreases when complementarities on height are removed, indicating a decrease in height inequality among children. In the second experiment, I compute children's counterfactual height-for-age z-score distribution under hypothetical marriage market preferences. Results from the simulation indicate that complementarity in height in the marriage market can increase the standard deviation of children's height distribution by up to 3% and, as a result, increase the prevalence of stunting by up to 4 percentage points. In other words, complementarity in height does not impact children's average height but does have a significant distributional effect and, as a result, can impact the stunting hazard and the inequality in children's height. To assess the magnitude of this result, Jayachandran and Pande (2017) find that due to strong eldest son preference in India, relative to their African counterparts, lower birth order children are on average 5 to 6 percentage points more likely to be stunted compared to their oldest sibling. I simulate a counterfactual scenario of no change in complementarity in height over time. I find a small change in the joint height distribution for the Scheduled Tribe and Muslim couples; however the impact on children's counterfactual potential height distribution is negligible.

To the best of my knowledge, this is the first paper to estimate preferences for height in the marriage market across religion-caste groups in India and to link the relationship between preferences for height in the marriage market to children's height distribution.

The rest of the paper is organized as follows. Section 2 summarizes the existing literature. Section 3 provides descriptive evidence regarding marital matching and sorting on height and quantifies the impact of parental height on children's height. Section 4 describes the model, identification and estimation strategy. Section 5 presents the estimation results, and Section 6 shows the counterfactual simulation results. Section 7 concludes the paper.

1950-1970. The young cohort consists of men born between 1970-1980 and married to women born between 1970-1990. I expand on the cohort selection procedure in Section 4.4.

[11] A child's potential height represents the transmission of height from parents to children and is used to measure a child's growth potential. Mid-parental height (average of the mother's and father's height) is frequently used by pediatricians to measure a child's potential height (Cole, 2000). Tanner's method (Tanner, Goldstein, and Whitehouse, 1970) uses mid-parental height, adjusted for a child's gender to measure a child's potential height. According to the WHO Multicentre Growth Reference Study (Garza, Borghi, Onyango, de Onis, and Group, 2013), potential height explains about 21% of the variability in linear growth from birth to 2 years of children in India.

2 Literature Review

This paper is related to the works studying marital matching and sorting in developing countries with a focus on anthropometric features, mechanisms driving child stunting, and changes in marital matching patterns over time.[12]

There is a growing body of work analyzing various aspects of the Indian marriage market.[13] In an insightful paper, Banerjee et al. (2013) develop a non-transferable utility model of the marriage market and estimate preferences for caste and other attributes using a unique dataset of upper-middle-class Indian families who placed matrimonial advertisements in a local newspaper in Kolkata (India).[14] The authors find strong preferences for within-caste marriage. The preferences for caste-endogamous are so strong that, bride's family is willing to trade off the difference between no education and a Master's degree in prospective groom to avoid marrying outside caste. This result leads me to model religion-caste groups as separate marriage markets. Differently, I model marriage markets in a transferable utility framework and structurally estimate preferences for height and other key attributes. Finally, while their data consists of mainly upper-caste families from a particular region of India, I use a nationally representative dataset to estimate marriage market preferences. In line with the finding that upper-middle-class men and women from Kolkata (India), prefer more educated spouses, I find strong positive assortative matching on education in religion-caste specific groups. Borker et al. (2017) model caste-specific marriage markets in a transferable utility framework and, using data from the rural population of Vellore district in Tamil Nadu (India), find significant positive assortative matching on wealth. Interestingly, conditional on wealth, the relation between the bride and the groom's education is insignificant. In line with their results, I see significant positive assortative matching on wealth; however, differently from their findings, I find significant cross-complementarity in husband's education and wife's natal family wealth in majority of caste-religion groups. In a recent paper, Beauchamp et al. (2017) model the Indian marriage market in a dynamic, general equilibrium, two-sided matching with non-transferable utility framework and estimate men's and women's preferences for education, age, and other attributes such as migration upon marriage, dowries, and preferences for an arranged marriage. Differently from their paper, I model the marriage market in a transferable utility framework and estimate preferences for anthropometric features along with cross-complementarity in education and height. One of the key results of their paper suggests that men's education is valued in the marriage market but not women's.[15] Though, I cannot identify men and women's preferences separately, I find significant complementarity in men and women's education across religion-caste groups and cross-complementarity in men's education and women's height, but not

[12]The importance of human capital investments on marital matching in developed countries is extensively analyzed, see Chiappori (2020) for an in-depth review.

[13]Likewise, there is abundant literature studying the importance of human capital investment in the marriage market in other developing countries. Using data from Indonesia and Zambia, Ashraf, Bau, Nunn, and Voena (2020) find that the likelihood of a girl being educated is higher among ethnic groups that practice bride-price and that families from bride-price groups are the most responsive to policies, like school construction, which are aimed at increasing female education. Boulier and Rosenzweig (1984) document positive assortative matching in the couple's educational levels using data from the Philippines. Fafchamps and Quisumbing (2005) report a positive correlation between spousal characteristics along, age, years of schooling, and parental land using data from rural Ethiopia. Boxho, Donald, Goldstein, Montalvao, and Rouanet (2020) find positive assortative matching on cognitive, socio-emotional skills and risk preference in rural Mozambique.

[14]Dugar, Bhattacharya, and Reiley (2012) take a similar approach and design a field experiment in which they place newspaper advertisements of potential grooms by varying caste and income. The authors document strong preferences for within-caste marriage but find that this preference decreases with the income of lower caste males.

Dupuy, Galichon, and Sun (2016) develop a novel methodology to estimate the affinity matrix as in Dupuy and Galichon (2014) when the data is high-dimensional. They apply their methodology to the data collected by Banerjee et al. (2013) and corroborate the finding of strong within-caste marriage preference.

[15]In a recent paper, Adams and Andrew (2019) illicit parental preferences and subjective beliefs about the importance of education and age in the marriage market in rural Rajasthan (India). They find that conditional on a marital match, parents seldom value their daughter's education. Parents believe that the probability of receiving a good match increases with their daughter's education but decreases with her age of leaving school.

vice-versa for majority of the caste-religion groups belonging to the young cohort.

Research focusing on the relevance of anthropometric features in the marriage market in developing countries remains sparse.[16] Using data from a popular dating website in China, Chiappori et al. (2021) track clicks on profiles with randomly assigned height and income and calculate men and women's willingness to pay for mate height. Their results indicate that men prefer taller women, and women prefer taller and higher-income men. In line with their results, I find significant positive assortative sorting on height; however, I find significant heterogeneity in cross-complementarity between men's height and women's family wealth and vice-versa in religion-caste specific groups.

Recent research has analyzed changes in marital matching patterns over time in the developing world, primarily focusing on education.[17] Evidence across the developing world regarding the increase in educational homogamy over time is mixed (Anukriti and Dasgupta, 2017). Smits and Park (2009), analyzing data from ten East-Asian societies, find that educational homogamy is higher at higher levels of education; however, since 1950 it has decreased for all levels of education, except the lowest level. In a recent paper studying the changes in assortative matching in Mexico, Hoehn-Velasco and Penglase (2021) find that educational homogamy among college graduates has grown substantially over time. Similarly, Ganguli, Hausmann, and Viarengo (2014) find that assortative matching on education increased from 1980 to 2000 in Latin American countries. I contribute to this research by studying changes in marital matching patterns along height.

Lastly, there is a vast strand of literature studying the determinants of children's height and stunting hazard. One of the key drivers of stunting in India is the child's disease environment and nutritional intake (Coffey et al., 2013a). Spears (2013) documents cross-country variation in sanitation and its role in explaining height differences across the globe. The author shows that a high rate of open defecation in India introduces germs in a child's environment that causes disease and stunts a child's growth. In an influential paper, Jayachandran and Pande (2017) show that the high rate of child stunting in India is primarily driven by strong eldest son preference. Higher birth order children in India, especially girls, have a significantly larger probability of stunting than their eldest brother compared to sub-Saharan countries. In an alternate mechanism affecting children's height, Calvi et al. (2021) find that an increase in women's control over household resources positively impacts their children's height in India. Finally, in a recent paper, Wang, Puentes, Behrman, and Cunha (2021) show that the height, parents target for their children depends on some reference population height, and parents make nutritional choices according to this target height. In their framework, reference height is an equilibrium object determined by an earlier cohort of children. Using data from a randomized control trial about a protein intervention in Guatemala, the authors show that 65% of the variation in height between the treatment and control group can be accounted by changes in the reference population height.

[16] Comprehensive research from developed countries studying the importance of anthropometric measures in the marriage market exists. In an influential paper, Chiappori et al. (2012) develop a model of the marriage market, in which individual preferences are summarized into a single index. Using data from the United States, the authors find that men compensate 1.3 additional units of body mass index (BMI) with a 1% increase in wages and women compensate two units of BMI with one year of education. Oreffice and Quintana-Domeque (2010) also document positive sorting on BMI, height, and weight using data from the United States. Hitsch, Hortaçsu, and Ariely (2010) estimate mate preferences in a non-transferable utility framework using the Gale-Shapley algorithm from an online dating site data, which includes users from North America and Europe. Their results specific to height indicate that men avoid tall women, whereas women prefer taller men. Dupuy and Galichon (2014) using data from the Netherlands, find positive assortative matching on BMI and height of men and women. Chiappori, Ciscato, and Guerriero (2020a) using data from Naples (Italy), document positive assortative matching on spouses' height and BMI.

[17] There is a growing strand of literature studying changes in marital sorting on education over time in the developed world. In the United States, preferences for partners with the same education has increased, especially for the highly educated (Fernández and Rogerson, 2001; Greenwood et al., 2014; Chiappori et al., 2017; Chiappori, Dias, and Meghir, 2020c; Ciscato and Weber, 2020). Chiappori, Costa-Dias, Crossman, and Meghir (2020b) do not observe an apparent change in assortativeness by education in the United Kingdom between 1945-54 and 1965-74.

3 Descriptive Evidence

The first part of this section establishes associations between men's and women's height, education, and parental education. The conditional correlations provide a valuable starting point to study the features along which marital matching and sorting happens in India. In the second part, I provide suggestive evidence regarding the impact of parental height on children's height conditional on household-level variables.

3.1 Determinants of Sorting

Table 1: Conditional Correlation: Matching on Height

	(1) Husband Height	(2) Wife Height
Wife Height	0.270***	
	(0.026)	
Wife Education	0.046	0.066**
	(0.029)	(0.029)
Husband Education	0.057**	0.042
	(0.021)	(0.027)
Husband Father Education	0.080***	0.027
	(0.024)	(0.033)
Wife Father Education	0.067*	0.004
	(0.036)	(0.023)
Husband Mother Education	-0.072	0.001
	(0.058)	(0.064)
Wife Mother Education	0.043	-0.029
	(0.042)	(0.031)
Husband Height		0.244***
		(0.024)
Region Fixed Effects	Yes	Yes
Year of Marriage Fixed Effects	Yes	Yes
Covariates	Yes	Yes
Observations	4,652	4,652
Mean of Dep. Variable	163.405	152.157

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: Covariates include religion, caste, age of the husband and age of the wife. Husband and wife's height is measured in centimeters. Education is measured in number of years. Standard errors are clustered at the state level.

In Table 1, I regress the husband's (wife's) height on spousal height controlling for other attributes such as education, parental education, and demographic characteristics such as caste, religion, state of residence, along with year of marriage fixed effects. We find a strong correlation in men and women's height, a one standard deviation increase in the women's height is associated with her having a 0.25 standard deviation taller husband (statistically significant at 1%). Similarly, a one standard deviation increase in men's height is associated with him having a 0.26 standard deviation taller wife (statistically significant at 1%).[18] We also observe a positive correlation between women's height and men's education and vice-versa; however, the coefficient is not statistically significant. Interestingly, we obtain a positive association between the wife's father's education and the husband's height, but the association between

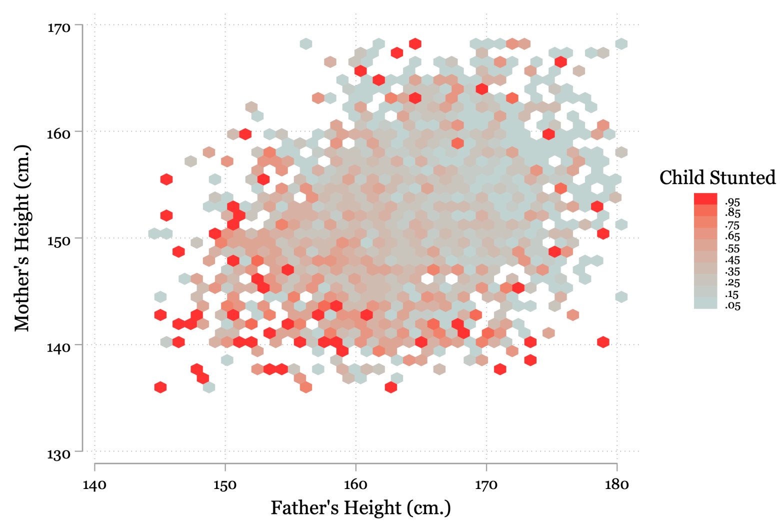
[18]In the appendix, Figure A2 shows the residual plot from a regression of husband's (wife's) height on all attributes similar to Table 1 excluding spousal height. Figure A3 shows a similar residual plot concerning education.

the husband's father's education and the wife's height is not statistically significant.

In the appendix, I perform a similar descriptive analysis concerning spousal education and parental education. Results from Table A1 indicate that a one standard deviation increase in women's education is associated with her having a husband with 0.52 standard deviations more education (statistically significant at 1%) and, a one standard deviation increase in men's education is associated with him having a wife with 0.4 standard deviations more education (statistically significant at 1%). We also see a positive correlation between a wife's height and a husband's education and vice-versa. Results from Table A2 and A3 provide suggestive evidence towards marital sorting on father's education and mother's education.

These results provide compelling descriptive evidence towards marital sorting on height, education, and parental education in India and the presence of asymmetric cross-complementarities in men and women's marriage market features.

Figure 1: Prevalence of Child Stunting by Parental Height



Note: The figure plots the prevalence of child stunting based on the mother's and the father's height in centimeters. A child with a height for age z-score two standard deviations or greater below the median world reference population for a given gender and age is considered stunted.

3.2 Children's Height and Parent's Height

The height for age z-score of a child is calculated with respect to the World Health Organization (WHO) reference scale.[19] A child with a height for age z-score two standard deviations or greater below the median world reference population for a given gender and age is considered stunted. Child stunting is widely recognized as a critical marker of child malnutrition (Deaton, 2007), which in turn has long-run consequences on individual well-being since child height is known to influence adult height, cognitive ability, and income (Tanner et al., 1956; Case and Paxson, 2008). The medical literature has shown height to be a highly heritable trait, with around 80% of the variation in height explained by genetics (Stulp and Barrett, 2016) and has provided evidence for a strong association between parental height and child stunting (Özaltin et al., 2010; Gupta, Cleland, and Sekher, 2021). Here I provide further descriptive evidence concerning the role of marital matching on height in determining children's height for age z-score.

Figure 1 plots the prevalence of child stunting with respect to parental height among children aged

[19] In particular, I calculate the height-for-age z-score for children of age 0 to 19 using 2007 WHO reference chart in STATA using the package *zanthro* (Vidmar, Cole, and Pan, 2013)

0-19 born to parents belonging to a particular marital cohort consisting of men born between 1970 and 1980 and women born between 1970 and 1990.[20] The figure suggests that parents with short stature are more likely to have stunted children, and as the mother and father's height increases, their children are less likely to be stunted.

However, parental height is highly correlated with other vital determinants of stunting such as educational attainment and household income.[21] To understand the role of parental height as a determinant of children's height, conditional on other key household-level and demographic determinants of children's height, in Table A5, I regress children's height for age z-score and stunting status on whether the parents are above or below median and height, parental education, parental age, household expenditure, whether the household has piped water, the mother's parent's literacy, the father's parent's literacy, child's gender, along with district fixed effects, religion-caste group fixed effects and age fixed effects. Household expenditure captures information regarding the child's nutritional intake and piped water and district fixed effects proxies a child's disease environment (Spears, 2013). Results indicate that *ceteris paribus*, the probability that a child with above the median-rank parents is stunted is 16 percentage points lower than a child with below-median rank parents. Similarly, a child with above-median rank parents has a 0.7 standard deviations greater height-for-age z-score than a child with below-median rank parents. Figure A23 illustrates the probability of stunting for children conditional on household-level characteristics for different combinations of parental height rank.

These results provide preliminary descriptive evidence regarding the role of parental height in determining the child's height conditional on key household-level variables. If preferences for height play a role in deciding who marries whom in the marriage market, then preferences for height in one generation will impact the next generation's height distribution and the prevalence of stunting.

In the next section, I estimate a structural to understand the role of preferences for height in the Indian marriage market. The model allows me to do counterfactual simulations and study how changes in preferences for height in the marriage market can impact children's height distribution.

4 Structural Analysis of Marital Matching

In order to understand the role of preferences for different marriage market attributes, I estimate a transferable utility model of the marriage market. The model identifies and estimates complementarity in height, education and parental education as well as cross-complementarity between them. The model is based on the framework of Dupuy and Galichon (2014). The structural estimation results will shed light on the features of men and women that are mutually attractive in the marriage market.

4.1 Transferable Utility Model of the Marriage Market

Consider a frictionless transferable utility environment.[22] Let H_x, E_x, FE_x, ME_x and A_x denote the height, educational attainment, father's education and mother's education, and the age of a man in the marriage market. Analogously, let H_y, E_y, FE_y, ME_y and A_y denote the women's characteristics. Therefore, every

[20] Section 4.4 describes in detail the sample selection procedure.

[21] Appendix Figure A6 shows a positive correlation between height and education for Indian men. Further, Table A24 shows a labor market height premium for Indian men, with the semi-elasticity of height being 0.08% comparable to what Case and Paxson (2008) find in the United States, but smaller than what Vogl (2014) finds in Mexico, ranging from 1.4% to 2.3%

[22] Therefore, we are assuming an environment in which utility can be transferred between partners at a constant rate.

man in the marriage market is characterized by a feature vector, $x = [H_x, E_x, FE_x, ME_x, A_x] \in \mathbb{R}^5$ and every woman in the marriage market is characterized by a feature vector , $y = [H_y, E_y, FE_y, ME_y, A_y] \in \mathbb{R}^5$. Let $P_x(.)$ and $Q_y(.)$ denote the probability distribution functions of x and y respectively, with $f_x(.)$ and $g_y(.)$ the corresponding probability density functions. A matching is defined as a probability density function, $\pi(x, y)$ of observing a couple from the matched population, in which, the man has a feature vector x, and the woman has a feature vector y.

Since we are in the transferable utility environment, a primitive of the problem is the joint surplus function. Define $\Phi(x, y)$ as the joint utility generated when a man with feature vector x marries a woman with feature vector y. Further, let $\Phi(x, \phi)$ denote the utility of a man with feature vector x if he remains single and $\Phi(\phi, y)$ utility of a woman with feature vector y if she remains single. The marital surplus, $s(x, y)$ is defined as $\Phi(x, y) - \Phi(\phi, y) - \Phi(x, \phi)$. Since singles are not observed in the data, $\Phi(\phi, y)$ and $\Phi(x, \phi)$ are normalized to zero. The main objective of the model is to identify the complementarities between different components of the feature vector x and y, normalizing the utility from remaining single to zero does not impede this.

In the data, we observe two men with the same feature vector x marrying two different women, with different feature vector y; this implies that matching is also occurring along features unobserved to the researcher. This requires the introduction of unobserved heterogeneity into the framework. The seminal paper of Choo and Siow (2006) considers the case when the attributes of men and women are discrete and scalar (for example, education level or age). In their framework, when a man m, of type x marries a woman w, of type y, the total joint utility produced is $\Phi(x, y) + \epsilon_{m|y} + \epsilon_{w|x}$. Let k_1 be the number of types for a man, and k_2 be the number of types for a woman.[23] Let $\epsilon_m = [\epsilon_{m|y_1}, \epsilon_{m|y_2}, .., \epsilon_{m|y_{k_2}}]$ be a $k_2 \times 1$ dimension vector of idiosyncratic shocks , and $\epsilon_f = [\epsilon_{f|x_1}, \epsilon_{f|x_2}, .., \epsilon_{f|x_{k_1}}]$ be a $k_1 \times 1$ dimension vector of idiosyncratic shocks, where, $\epsilon_{m|y_k}$ is the idiosyncratic shock that a man m draws on matching with a woman of type y_k. This represents his idiosyncratic preference for a type y_k woman that the researcher does not observe. Analogously, $\epsilon_{f|x_k}$ is the idiosyncratic shock that a woman f draws on matching with a man of type x_k. Choo and Siow (2006) model ϵ_m and ϵ_f as independent and identically Gumbel distributions with scaling parameter $\frac{\sigma}{2}$. As a result, the joint utility, when a man of type x marries a woman of type y can be divided as $\Phi(x, y) = U(x, y) + V(x, y)$, where the utility of a man m of type x on matching with a woman w of type y is $U(x, y) + \epsilon_{m|y}$ and utility of a woman w of type y on matching with a man m of type x is $V(x, y) + \epsilon_{w|x}$. In this framework, an individual's utility in equilibrium depends on their own and their potential partner's observable attributes.

In our context, individuals are matching on a multidimensional feature vector, in which some of the features like height are continuous variables. Dupuy and Galichon (2014) extend the framework of Choo and Siow (2006) to continuous multidimensional features. The approach is as follows: Each man m of type x in the marriage market draws a random, infinite, but countable subset of potential partners. Each potential partner for a man m is defined by a feature vector $[y_k^m, \epsilon_k^m] \in \mathbb{R}^5 \times \mathbb{R}$, where y_k^m is the vector of observable characteristics and ϵ_k^m is the random sympathy of a randomly drawn woman. Therefore, if a man m with feature vector x marries a woman with feature vector y_k^m from his randomly drawn subset, he receives a utility $U(x, y_k^m) + \frac{\sigma}{2}\epsilon_k^m$. Each man with a feature vector x, solves the following discrete choice problem,

$$\max_k \quad U(x, y_k^m) + \frac{\sigma}{2}\epsilon_k^m.$$

[23] for example, if we consider types by education levels, and each man is either a college graduate or not, and similarly each woman is either a college graduate or not, then $k_1 = 2$ and $k_2 = 2$.

Finally, we need to specify the random process according to which every man draws his set of potential partners. Assume that the vector $[y_k^m, \epsilon_k^m]$ is an enumeration of a Poisson process on $\mathbb{R}^5 \times \mathbb{R}$ with intensity $dy \times e^{-\epsilon} d\epsilon$. Analogously, each woman w of type y draws a random subset of infinite but countable subset of potential partners. Each potential partner of a woman is defined by a feature vector $[x_l^w, \eta_l^w] \in \mathbb{R}^5 \times \mathbb{R}$. If a woman with feature vector y marries a man with feature vector x_l^w from her randomly drawn subset, she receives a utility $V(y, x_l^w) + \frac{\sigma}{2}\eta_l^w$. Each woman with a feature vector y solves the following discrete choice problem,

$$\max_l \quad U(x_l^w, y) + \frac{\sigma}{2}\eta_l^w.$$

As in the case of men, the vector $[x_l^w, \eta_l^w]$ is assumed to be an enumeration of a Poisson process on $\mathbb{R}^5 \times \mathbb{R}$ with intensity $dx \times e^{-\eta} d\eta$. Dupuy and Galichon (2014) show that by assuming partners are drawn randomly from a Poisson process leads to a continuous multinomial logit choice model.[24] Therefore, the probability of a man m with feature vector x, choosing a woman with feature vector y from his randomly drawn set is given by,

$$\pi(y|x) = \frac{e^{[U(x,y)/(\sigma/2)]}}{\int_{\mathbb{R}^5} e^{[U(x,t)/(\sigma/2)]} dt}.$$

Similarly, the probability of a woman w with a feature vector y choosing a man with feature vector x from her randomly drawn set is given by,

$$\pi(x|y) = \frac{e^{[V(t,y)/(\sigma/2)]}}{\int_{\mathbb{R}^5} e^{[V(t,y)/(\sigma/2)]} dt}.$$

This leads to the key equation relating the equilibrium match probabilities $\pi(x, y)$ and the joint utility $\Phi(x, y)$,

$$\log \pi(x, y) = \frac{\Phi(x, y) - a(x) - b(y)}{\sigma}. \tag{1}$$

The share of the joint utility allocated to the man is given by,

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

and the share of the joint utility allocated to the woman is given by,

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

4.2 Identification of Complementarities

The identification question is as follows: Given the data on the equilibrium match distribution, can the joint utility function $\Phi(x, y)$ be identified? From equation A1 and equation A2, we can write:

$$\begin{aligned}
U(x, y) &= \frac{\sigma}{2}[\log(\pi(y|x) + c(x)] \\
V(x, y) &= \frac{\sigma}{2}[\log(\pi(y|x) + d(y)] \\
\Phi(x, y) &= U(x, y) + V(x, y) = \frac{\sigma}{2}[\log(\pi(y|x) + \log(\pi(y|x) + c(x) + d(y)],
\end{aligned}$$

[24] See appendix Section A.2 for the derivation.

as a result, the joint utility is identified only up to the unknown additive functions $c(x)$ and $d(y)$.[25] Therefore, the joint utility function, $\Phi(x, y)$ is not identified from the equilibrium match distribution without additional assumptions. The identified object is the cross-derivative of the joint utility function with respect to x and y. Taking the derivative of equation 1 with respect to x and y gives, $\frac{\partial^2\Phi(x,y)}{\partial x \partial y} = \frac{\partial^2 \log \pi(x,y)}{\partial x \partial y}$.[26] Therefore, the identified object is the cross-derivative of the joint utility function with respect to men's and women's marriage market features. The second derivative of the joint marital utility concerning x and y is precisely the object of interest as it captures the complementarities between any two marriage market features.

4.3 Estimation of Complementarities

Since the feature vectors of men and women in the marriage market consist of continuous variables like height, non-parametric estimation is not feasible. Therefore, the joint utility, $\Phi(x, y)$, is parameterized as the following function:

$$\Phi(x,y) = x^T A y \tag{2}$$

$$= \begin{bmatrix} H_x & E_x & FE_x & ME_x & A_x \end{bmatrix}^T \begin{bmatrix} \lambda_{HH} & \lambda_{HE} & \lambda_{HFE} & \lambda_{HME} & \lambda_{HA} \\ \lambda_{EH} & \lambda_{EE} & \lambda_{HFE} & \lambda_{HME} & \lambda_{HA} \\ \lambda_{FEH} & \lambda_{FEE} & \lambda_{FEFE} & \lambda_{FEME} & \lambda_{FEA} \\ \lambda_{MEH} & \lambda_{MEE} & \lambda_{MEFE} & \lambda_{MEME} & \lambda_{MEA} \\ \lambda_{AH} & \lambda_{AE} & \lambda_{AFE} & \lambda_{AME} & \lambda_{AA} \end{bmatrix} \begin{bmatrix} H_y \\ E_y \\ FE_y \\ ME_y \\ A_y \end{bmatrix}, \tag{3}$$

where matrix A is the critical component of interest known as the *affinity matrix*. From the previous section, the identified object is the cross-derivative of $\Phi(x, y)$ with respect to x and y. This object is precisely the affinity matrix. In our context, A is a 5×5 matrix. Recall that each man and each woman in the marriage market is characterized by a 5×1 feature vector, namely, height, education, father's education, mother's education and age. Each element of A, λ_{ij} represents the strength of attractiveness or repulsiveness between the man's feature x_i and the woman's feature y_j. It is the increase in the joint utility when the i^{th} element of man's feature vector x and the j^{th} element of the woman's feature vector are increased by one unit. Therefore, each of the λ_{ij} represents the complementarity or substitutability between the two attributes i and j in the joint utility function. Our main parameters of interest are λ_{HH}, λ_{HE} and λ_{EH} representing the complementarity in men and women's height, cross-complementarity in men's height and women's education and cross-complementarity in men's education and women's height.

Galichon and Salanié (2020) and Dupuy and Galichon (2014) show that the equilibrium matching in the presence of unobserved heterogeneity can be written as,

$$Z(A,\sigma) = \max_{\pi \in P \times Q} \int\int_{\mathbb{R}^5 \times \mathbb{R}^5} x^T A y \, \pi(x,y) dx dy - \sigma \int\int_{\mathbb{R}^5 \times \mathbb{R}^5} \log \pi(x,y) \pi(x,y) dx dy. \tag{4}$$

Intuitively, as explained in Galichon and Salanié (2020) the first term explains the part of the surplus that comes from the interaction between observable characteristics. In contrast, the second term represents the unobservable heterogeneity in tastes. Maximizing equation 4 is equivalent to maximizing

[25] Where, $c(x) = \log(\int_{\mathbb{R}^4} e^{[U(x,t)/(\sigma/2)]} dt)$ and $d(y) = \log(\int_{\mathbb{R}^4} e^{[V(t,y)/(\sigma/2)]} dt)$.

[26] Note that $\frac{\partial^2\Phi(x,y)}{\partial x \partial y}$ is a Jacobian, since x and y are vectors.

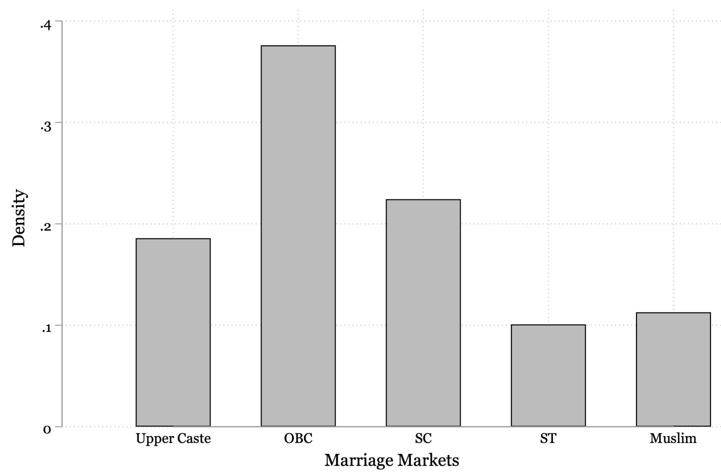
$Z(A/\sigma, 1)$, which leads to the following convex optimization problem, with $B = A/\sigma$,

$$\min_B Z(B,1) - \mathbb{E}_{\hat{\pi}}(x^T B y), \tag{5}$$

where, $\hat{\pi}$ are the observed match probabilities in the data. This is a moment matching estimator, in which the moments predicted by the optimal matching function $\pi(x, y)$ are matched to the empirical moments. Therefore, B is computed so that, $\mathbb{E}_{\hat{\pi}}[XY^T] = \mathbb{E}_{\pi}[XY^T]$, where $\mathbb{E}_{\hat{\pi}}[XY^T]$ is the cross-covariance matrix between men and women's marriage market features in the data, and $\mathbb{E}_{\pi}[XY^T]$ is the cross-covariance matrix predicted by the model. Since matrix A is identified up to a scale, I normalize σ to 1. The standard errors of elements of the affinity matrix are calculated using the inverse of the Fisher information matrix, which is computed numerically as the Hessian matrix of $Z(A, 1)$ in equation 4.

4.4 Data

Figure 2: Religion-Caste Group Distribution



Note: This figure shows the distribution of religion-caste groups in the sample. OBC stands for the Other Backward Caste, SC stands for the Scheduled Caste, and ST stands for the Scheduled Tribe.

The Indian Human Development Survey (IHDS) is a nationally representative panel study containing detailed economic and demographic information. The first wave of the IHDS was collected in 2005-2006 and the second wave in 2011-2012. The key feature of the second wave of the IHDS that makes it ideal for my analysis is that the IHDS II, as far as I know, is the only nationally representative dataset that contains information on the wife and the husband's height along with details about *both* marital and natal family.[27]

IHDS II is a multi-topic survey of 42,152 households in 1503 villages and 971 urban neighborhoods across India. For every individual in the household, anthropometric features, educational attainment, and age are measured; however, information regarding natal and marital family is measured for a subset of eligible women. In particular, for 39,523 eligible women, information regarding the women's parental education and her husband's parental education is measured in the number of years. The data also provides information regarding the natal family's wealth level relative to the marital family for eligible

[27] The first wave of the IHDS has information on women's height, but information on men's height is missing in the majority of the sample.
The 2005 and 2015 wave of the National Family Health Survey(NFHS) has information on the wife and husband's education, height, and age but doesn't include information regarding the natal family. The 2006 wave of the Rural Economic and Demographic Survey (REDS) is a nationally representative data of *rural* India and also contains information regarding both natal and marital family along with information on height. I use the 2006 wave of REDS for secondary analysis.

women. I use the father's education as a proxy for family wealth and family status and the mother's education as a proxy for the gender attitudes of the family (Dhar, Jain, and Jayachandran, 2019).

Defining marriage markets to study the nature of sorting along various attributes is a non-trivial issue (Chiappori et al., 2017; Ciscato and Weber, 2020). I define a marriage market with respect to a religion-caste group and men's year of the birth cohort. In particular, I define two cohorts: Cohort one, which I refer to as the young cohort, consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990, with the age gap ranging from zero to ten.[28] Cohort two, which I refer to as the old cohort, consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970, with the age gap between them ranging from zero to thirteen.[29] Couples belong to one of the five religion-caste groups, namely, Scheduled Caste (SC), Scheduled Tribe (ST), Other Backward Caste (OBC), Upper Caste, or Muslims. Given the fact that marriages in India are primarily endogamous (Banerjee et al., 2013; Borker et al., 2017), I model each caste-religion group as a separate marriage market. In particular, I define ten marriage markets, religion-caste-cohort specific. From the sample of 39,523 eligible women, I select a sample of couples with non-missing information on height, education, parental education, and age, belonging to one of the ten religion-caste-cohort-specific marriage markets. The final sample consists of 7355 couples.

From Figure 2, 48% of the sample belongs to the Other Backward Caste, 22% belong to the marginalized Scheduled Caste, 10% belong to Scheduled Tribe, 19% belong to Upper Caste, and 11% are Muslims. Table A4 shows the summary statistics for the selected sample. From Table A4, men's average height is 163 centimeters, and women's average height is 152 centimeters, with the average height gap between the husband and the wife being 11 centimeters. Men's median education is seven years, and women's is three years. The average education gap between couples is two years. Parental educational attainment in both marital and natal families is low. The median husband and wife's father and the median husband and wife's mother have zero years of education. In 17% of the couples, the natal family is wealthier than the marital family. Figure A1 shows the raw correlations between the husband and the wife's marriage market features. From A1(A), we see a positive correlation in the husband and the wife's height across religion-caste groups. Similarly, we also observe a positive correlation between the husband and the wife's education, the father's education, and the mother's education.

Next, I show the results for the estimated affinity matrix defined in equation 2 for religion-caste-cohort-specific marriage markets.

5 Estimation Results

The model is estimated for the young cohort and the old cohort separately. All the features are standardized to have a mean of zero and a standard deviation of one. I describe the results for the young cohort first. Table 2 shows the affinity matrix estimates for the biggest religion-caste group in the sample, Other Backward Caste. The affinity matrix reveals several interesting results. First, we find strong complementarity in men's and women's height. A one standard deviation increase in men's height and a one standard deviation increase in women's height increases the joint utility by 0.31 units (statistically

[28] 99% of the couples belonging to the young cohort have an age gap between zero and ten. Therefore, the spouse's year of birth spans from 1970 to 1990.

[29] 99% of the couples belonging to the young cohort have an age gap between zero and thirteen. Therefore, the spouse's year of birth spans from 1950 to 1970.

Table 2: Affinity Matrix Estimates: Other Backward Caste (Young Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.305*** (0.03)	0.022 (0.036)	0.089*** (0.034)	-0.001 (0.033)	0.217*** (0.051)
Education	0.105*** (0.038)	0.664*** (0.048)	0.14*** (0.042)	0.036 (0.043)	0.111** (0.065)
Father Education	0.007 (0.034)	0.063* (0.041)	0.187*** (0.035)	0.006 (0.035)	0.074* (0.057)
Mother Education	0.011 (0.034)	0.195*** (0.044)	-0.048 (0.034)	0.161*** (0.028)	-0.043 (0.058)
Age	0.159*** (0.05)	0.396*** (0.062)	-0.171 (0.057)	0.085* (0.054)	2.63*** (0.113)

Note: Each element represents the complementarity/ substitutability between two features. The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 3: Affinity Matrix Estimates: Upper Caste (Young Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.31*** (0.048)	-0.033 (0.065)	0.087** (0.047)	-0.044 (0.041)	0.071 (0.076)
Education	0.081 (0.064)	0.975*** (0.098)	0.132** (0.064)	0.043 (0.06)	0.082 (0.103)
Father Education	0.041 (0.05)	0.033 (0.07)	0.283*** (0.047)	-0.038 (0.041)	0.046 (0.08)
Mother Education	-0.061 (0.043)	0.274*** (0.064)	-0.009 (0.039)	0.107*** (0.029)	0.046 (0.068)
Age	-0.045 (0.074)	0.262*** (0.103)	-0.159 (0.075)	0.131** (0.062)	2.195*** (0.152)

Note: Each element represents the complementarity/ substitutability between two features. The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

significant at 1%). This indicates that taller men and taller women find each other mutually attractive in the marriage market. Second, we find significant positive assortative matching concerning education; a one standard deviation increase in the husband's education and a one standard deviation increase in the wife's education increases the marital surplus by 0.664 units. Therefore, for the OBC marriage market, the complementarity in height is approximately half the complementarity in education. Third, strong complementarity is also observed concerning parental education. A one standard deviation increase in the wife's father's education and a one standard deviation increase in the husband's father's education increases the joint marital utility by 0.16 units. Similarly, a one standard deviation increase in the wife's mother's education and a one standard deviation increase in the husband's mother's education increases the joint marital utility by 0.13 units. Since I use father's education as a proxy for family wealth, this result suggests positive assortative matching on wealth in line with Borker et al. (2017), who document positive assortative matching along wealth for caste-specific marriage markets. Finally, complementarity on age have the biggest magnitude. This finding primarily reflects the presence of multiple cohorts in the

Table 4: Affinity Matrix Estimates: Scheduled Tribe (Young Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.403***	-0.057	-0.012	0.07	-0.03
	(0.061)	(0.065)	(0.083)	(0.096)	(0.091)
Education	0.03	0.778***	0.145*	-0.257	-0.009
	(0.076)	(0.088)	(0.101)	(0.114)	(0.117)
Father Education	0.054	-0.019	0.252**	0.132	0.267**
	(0.099)	(0.11)	(0.113)	(0.113)	(0.152)
Mother Education	0.008	0.114	0.01	0.074	-0.3
	(0.099)	(0.11)	(0.108)	(0.097)	(0.15)
Age	-0.07	0.113	-0.166	0.258**	2.092***
	(0.085)	(0.095)	(0.122)	(0.131)	(0.165)

Note: Each element represents the complementarity/ substitutability between two features. The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 5: Affinity Matrix Estimates: Scheduled Caste (Young Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.284***	0.082***	0.078***	-0.1	0.215***
	(0.037)	(0.041)	(0.045)	(0.057)	(0.056)
Education	0.018	0.686***	0.131***	0.084	0.12*
	(0.049)	(0.057)	(0.055)	(0.072)	(0.076)
Father Education	-0.022	0.191***	0.222***	-0.084	-0.012
	(0.046)	(0.052)	(0.046)	(0.061)	(0.07)
Mother Education	0.048	0.077	-0.028	0.267***	-0.056
	(0.06)	(0.071)	(0.057)	(0.051)	(0.091)
Age	0.036	0.225***	-0.137	0.116*	2.29***
	(0.061)	(0.069)	(0.073)	(0.089)	(0.119)

Note: Each element represents the complementarity/ substitutability between two features. The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

estimation sample and people marrying individuals from similar cohorts (Chiappori et al., 2020a).

A key point to note is the asymmetry of the affinity matrix. For example, the cross-complementarity in men's education and women's height is 0.105 and statistically significant at 1%, whereas the cross-complementarity in men's height and women's education is statistically insignificant. This result indicates that more educated men and taller women find each other mutually attractive in the marriage market, but not vice-versa. One of the possible channels driving this result is as follows: The anthropology literature in developing countries has also documented a positive relationship between reproductive success (lower infant mortality rates) and women's height due to the physiological benefits of being tall (Sear, 2006). This relationship becomes especially critical in high disease environments with poor health infrastructure, where the risk of infant mortality is high. In India, high rates of infant mortality have been linked to neighborhoods with poor sanitation and high disease prevalence (Geruso and Spears, 2018). Following Becker (1973), if we consider the joint utility in the transferable utility framework to represent child quality, which is inversely related to infant mortality, then we would expect taller women due to their

Table 6: Affinity Matrix Estimates: Muslims (Young Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.434***	-0.009	-0.081	0.101*	0.351***
	(0.059)	(0.068)	(0.071)	(0.074)	(0.09)
Education	0.106*	0.785***	0.105	0.064	0.049
	(0.075)	(0.091)	(0.091)	(0.101)	(0.117)
Father Education	-0.052	0.164**	0.41***	-0.082	-0.19
	(0.071)	(0.083)	(0.076)	(0.083)	(0.112)
Mother Education	-0.014	0.223***	-0.201	0.234***	0.091
	(0.076)	(0.087)	(0.072)	(0.061)	(0.115)
Age	-0.019	0.323***	-0.39	0.133	2.2***
	(0.086)	(0.102)	(0.107)	(0.111)	(0.169)

Note: Each element represents the complementarity/ substitutability between two features. The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

higher reproductive success to be more preferred in the marriage market.

We also observe strong cross-complementarity in men's height and women's father's education, and in men's education and women's father's education. This result indicates that wealthier natal families and taller and more educated men find each other more attractive in the marriage market. This finding is in line with Chiplunkar and Weaver (2019) who find that more educated men receive a more considerable dowry in the marriage market in India. We also find cross-complementarity in men's father's education and women's education (statistically significant at 10%); however, the cross-complementarity in men's father's education and women's height is statistically insignificant. Interestingly, we also observe cross-complementarity between men's mother's educational attainment and women's educational attainment. Since the mother's education potentially reflects the family's gender attitudes in line with Dhar et al. (2019), this result demonstrates that marital families with more progressive gender attitudes and women with higher educational levels find each other mutually attractive in the marriage market.[30]

Tables 4 and 5 show the affinity matrices for the marginalized and economically backward groups in India, the Scheduled Caste and the Scheduled Tribe. Similar to the Other Backward Caste, we find positive assortative matching on height for both groups. The estimated complementarity in height for the SC sample is 0.28, and for the ST sample is 0.4. In contrast to the other religion-caste-specific marriage markets, for the Scheduled Caste couples, we observe cross-complementarity in men's height and women's education but not vice-versa. For the Scheduled Tribe couples, the cross-complementarity in men's height and women's education and vice-versa is not statistically significant. Therefore, this result demonstrates important heterogeneities in the affinity matrix among different religion-caste-specific marriage markets. For the Scheduled Caste and Scheduled Tribe couples, we find cross-complementarity in men's education and natal family wealth. For the Scheduled Caste couples, we also find cross-complementarity in marital family wealth and women's education. Lastly, we find cross-complementarity in men's height and women's

[30] A well-documented feature when matching on height is the male-taller norm. The male-taller norm refers to the fact that women prefer their potential partners to be taller than them, and men, in turn, prefer their potential partners to be shorter than them. The male taller norm has been documented in several developed countries(Gillis and Avis, 1980; Courtiol et al., 2010). In our sample, we see a strong adherence to the male taller norm. In 95% of the couples, the husband is taller than the man. One of the potential channels leading to the significant positive assortative matching on height is the male-taller-norm. However, the strong cross-complementarity between men's height and natal family wealth and the presence of cross-complementarity between men's education and wife's height indicates a role for height in the marriage market beyond the male-taller-norm. As a result, it is unlikely that the results are being driven solely by adherence to the male-taller norm.

natal family wealth for the Scheduled Caste couples.

Tables 3 shows the affinity matrix for the Upper Caste group. The estimated complementarity in height is 0.3. Results also indicate that taller and more educated men and wealthier natal families find each other mutually attractive in the marriage market. Similar to the results for the Other Backward Caste couples, more educated women and gender progressive marital families are mutually attractive in the marriage market. The estimated coefficient for the cross-complementarity between men's education and women's height is positive but not statistically significant. Interestingly, the complementarity in education is the highest for the Upper Caste couples. In other words, the degree of positive assortative matching on education is the highest in the Upper Caste marriage market.

From Table 6, for the Muslim marriage market, a one standard deviation increase in men's height and a one standard deviation increase in women's height increases the joint marital surplus by 0.403 units (statistically significant at 1%). We also observe positive assortative matching concerning education and parental education. Similar to the Other Backward Caste and Upper Caste couples, we also find cross-complementarity in men's education and women's height, implying more educated men and taller women see each other as mutually attractive. Finally, similar to the Other Backward Caste couples, marital families with gender progressive attitudes and more educated women find each other mutually appealing in the marriage market. Interestingly, the complementarity in height is the highest for Muslims in India. In other words, the degree of positive assortative matching on height is the highest in the Muslim marriage market.[31]

Tables A7, A8, A9, A10 and A11 show the affinity matrix estimates corresponding to various religion-caste specific groups for the old cohort. Overall, we observe strong positive assortative matching on height in every marriage market. We also see significant positive assortative matching with respect to education and parental education across marriage markets. However, cross-complementarity between various features shows significant heterogeneities across different religion-caste-specific marriage markets. For example, we see a positive and statistically significant cross-complementarity between men's education and women's height in the Muslim marriage market, but the cross-complementarity between men's education and women's height is insignificant in the remaining caste-specific marriage markets. In all the marriage markets concerning the old cohort, we observe a positive cross-complementarity between men's education and women's fathers' education. We also find cross-complementarity on men's fathers' education and women's education. Lastly, the results suggest positive cross-complementarity with respect to men's mothers' education and women's education. Overall, the results suggest significant heterogeneity in marriage markets across religion, caste, and time.

Table 7: Changes in Complementarity in Height: Comparison Tests

	Complementarity in Height Young Cohort	Complementarity in Height Old Cohort	Change in Complementarity	t-statistic (p-value)
Upper Caste	0.31	0.31	-0.0005	-0.0079 (0.496)
Other Backward Caste	0.305	0.264	0.038	0.865 (0.194)
Scheduled Tribe	0.403	0.232	0.167*	1.5 (0.067)
Muslims	0.434	0.272	0.157**	1.69 (0.045)
Scheduled Caste	0.284	0.319	-0.033	-0.529 (0.298)

Note: The young cohort consists of men born between 1970 and 1980 and their spouses born between 1970 and 1990. The old cohort consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970. Standard errors for the difference in complementarity is computed using bootstrap with 500 draws. * $p < 0.1$, ** $p < .05$, *** $p < 0.01$.

[31] I do not discuss the potential mechanisms driving this result as its beyond the scope of the paper. Future work will attempt to provide a channel for this result.

Changes in Complementarity over Time: Having estimated the complementarities between various features for the young and old cohorts, a natural question arises: How have complementarities on height in different marriage markets evolved over time?

This question is motivated by an interesting observation that the height of Indians irrespective of gender, caste, or religious group has increased very marginally. To emphasize this puzzling fact, figure A25 compares the trajectory in the development of education and height for three developing countries, China, Mexico, India, and one developed country, the United States. The trend in the educational outcome as measured by the number of primary age children enrolled in primary school follows a similar increasing trajectory across the three developing countries. However, when comparing China and Brazil to India, the trend in height paints a different picture. The height of Chinese and Brazilian men has increased by five centimeters between 1940 and 1990, whereas the height of Indian men has increased by only two centimeters. Similarly, the height of Chinese and Brazilian women has risen by four centimeters between 1940 and 1990, whereas the height of Indian women has grown by only two centimeters. One of the key factors driving this result is the differential evolution in the disease environment and health infrastructure across the three countries. High rates of open defecation in India have been linked to child stunting (Spears, 2013; Coffey and Spears, 2017).

Given the evolution of height in India, I study how preferences for height have evolved in India across religion-caste groups. More precisely, I compare the complementarity parameter in the affinity matrix corresponding to height for the old cohort and the young cohort. Table 7 shows the complementarity in height parameter for the old cohort and the young cohort, along with the change in the complementarity in height across religion-caste-specific marriage markets. The most significant increase in complementarity in height is observed for the Scheduled Tribe, followed by Muslims. In other words, considering the changes in the marginal distribution of men and women's height, taller men and taller women belonging to the young cohort find each other more attractive in the marriage market than taller men and taller women belonging to the old cohort. We see a marginal increase in the complementarities in height for the Other Backward Caste couples but the difference is not statistically significant. Complementarities in height show no significant change for the Upper Caste and the Scheduled Caste couples. These results indicate a considerable degree of heterogeneity across religion-caste groups in the evolution of complementarities for height in the marriage market in India.

Saliency Analysis: The affinity matrix helps understand the degree of complementarity/substitutability between various marriage market features. Next, I quantify the relative importance of each of these features in explaining the marital surplus using the saliency analysis technique developed by Dupuy and Galichon (2014).[32] From Table A15, for the largest religion-caste-specific marriage market, height primarily loads on Index 3 for men and women, which explains approximately 8% of the variation in the joint marital surplus from Table A14. In comparison, education primarily loads on Index 2 for men and women, which explains approximately 16% of the variation in the joint marital surplus. Therefore, relative to education, height explains about half the variation in the joint marital utility. Similarly, from Table A18, A19, A20 and, A21 for the Scheduled Tribe and Muslim couples, height explains about 11% of the observed joint marital utility, which is about half the variation explained by education. For the Scheduled Caste couples, height explains about 8% of the variation in the martial surplus, compared to 19% explained by education. Lastly, for the Upper Caste couples, height and father's education primarily load

[32]The procedure is detailed in the appendix, Section A.1.

onto Index 3 and Index 4 for men and women. Index 3 and Index 4 explain about 25% and 12% of the variation in the joint marital surplus, respectively. Therefore, since height does not load independently onto an index for the Upper Caste couples, it is not possible to obtain the portion of the marital surplus explained by height independently. Overall we can conclude that, on average, in India, height explains about half the variation in the joint marital surplus compared to education.

Robustness Checks: In the appendix, I perform several robustness checks. First, I re-estimate the model using the REDS,2006 dataset and show that the results regarding the strong complementarities in height are qualitatively unchanged. The REDS, 2006 is a nationally representative sample of rural India. Unlike the IHDS, the REDS 2006 measures family wealth in terms of family landholdings.[33] Table A12 and A13 show the results for the Other Backward Caste and the Upper Caste sample.

Second, I re-estimate the model for individuals living in rural and urban India separately and show that the strong complementarities in height are qualitatively unchanged. Ideally, we would estimate our model concerning religion-caste groups living in a particular district, since a large portion of marriages in India take place within a district, with the average travel time between marital and the natal family home being three hours (Rosenzweig and Stark, 1989; Fulford, 2013; Beauchamp et al., 2017). However, the sample size prevents the estimation of the model at the district level. The results related to positive assortative matching on height, education, and parental education are qualitatively confirmed when the model is separately estimated for the rural and urban. However, the cross-complementarity shows significant heterogeneities across rural and urban areas (Results not shown for brevity but are available upon request). Lastly, since a father's education is an imperfect measure of family wealth, I estimate the model separately for a subsample in which the marital and natal families have the same wealth level. This constitutes 83% of the sample. Results are qualitatively confirmed for this subsample and are available upon request.

6 Counterfactual Simulations

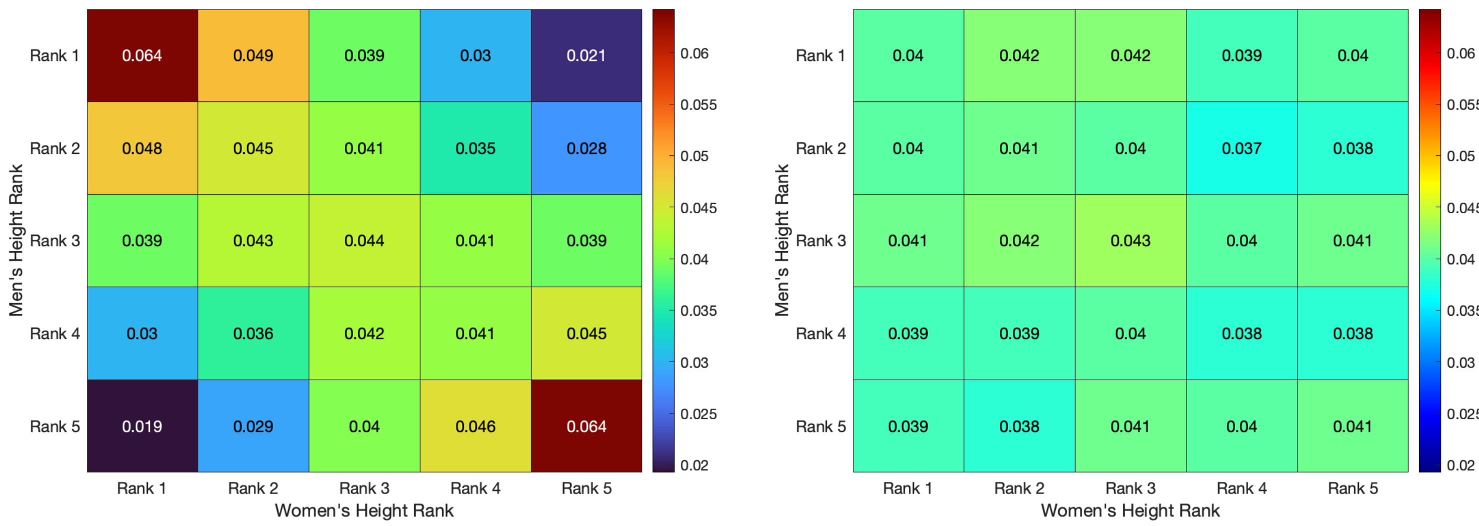
Using the affinity matrix estimates, I simulate various hypothetical preferences for height in the marriage market and compute couple's joint height distribution. To understand the implications of matching on height, I study how one generation's preferences for height in the marriage market can influence the next generation's height distribution.

6.1 No Complementarity in Height

I simulate a hypothetical marriage market in which men and women show no complementarity in height, contrary to what the results in Section 5 have shown. I set the parameter capturing the complementarity in height to zero in each religion-caste-specific marriage market and estimate the counterfactual equilibrium match distribution. This corresponds to setting λ_{HH} in equation 2 to zero. Note that all other elements of the affinity matrix are unchanged. I plot the couple's joint height distribution under this hypothetical scenario. To illustrate the results, I divide men and women into five height ranks. Rank 1 represents men (women) in the top 20th percentile of the men's (women's) height distribution, rank 2 20th-40th

[33] Information regarding the husband and the wife's height and natal and marital family wealth is available only for the household head and his spouse. Data regarding family wealth is missing for a significant portion of the sample; as a result, the sample size of REDS, 2006 is significantly smaller than the IHDS.

Figure 3: Matching on Height (Other Backward Caste): No Complementarity



(A) Predicted Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Plot (A) shows the actual Rank-Rank matching and plot (B) shows the counterfactual Rank-Rank matching if there was no complementarity in height in the marriage market. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

percentile, rank 3 40th-60th percentile, rank 4 60th-80th percentile, and rank 5 the top 20th percentile.

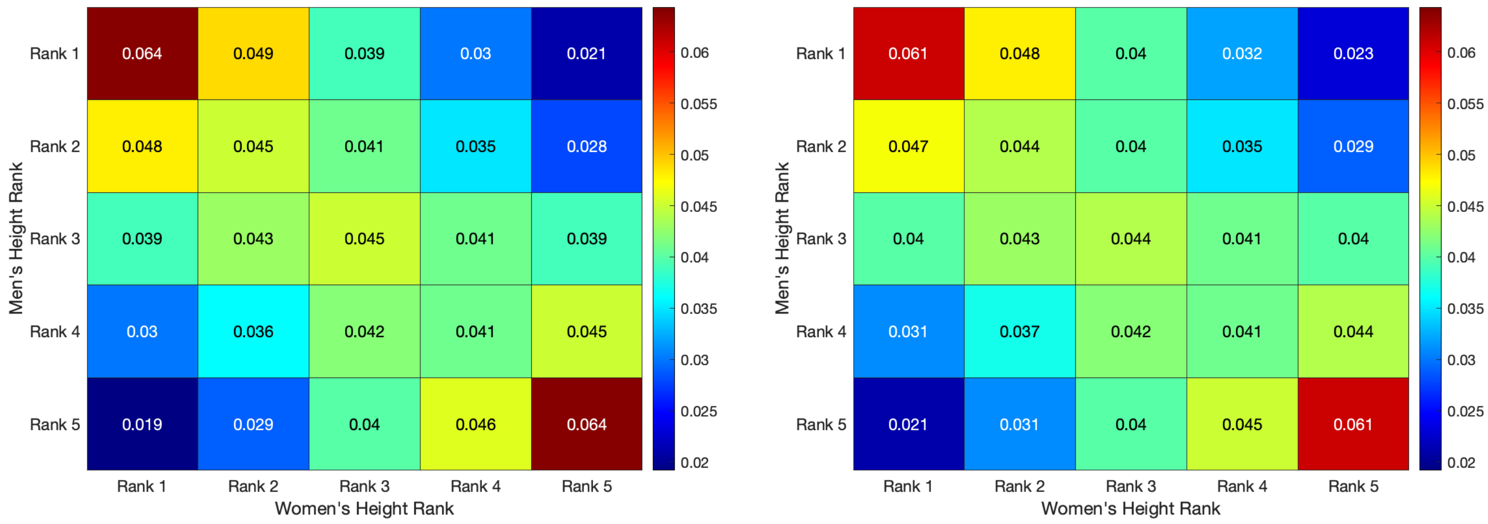
Figure 3 shows the predicted rank-rank matching versus the counterfactual rank-rank matching for the largest religious-caste group in the sample, the Other Backward Caste. From Figure 3(A), under the actual equilibrium matching, the probability of a height rank one woman marrying a height rank one man, and the probability of a rank five-man marrying a rank five-woman is six percent. The likelihood of a rank one man marrying a rank five woman and vice-versa is two percent. From Figure 3(B), when the complementarity in height parameter is set to zero, the probability of a height rank five-man marrying a height rank five-woman and a height rank one-man marrying a height rank one-woman drops to four percent. Similarly, the likelihood of a rank one man marrying a rank-five woman and vice-versa increases by approximately two percentage points. Overall when the complementarity in the height parameter is zero, the couple's joint height distribution is approximately uniform.

In the Appendix, Figures A4, A5, A6 and A7 show similar results for the remaining religion-caste-specific marriage markets. Further, in the Appendix, I simulate a similar counterfactual, wherein I set the complementarities in height parameter equal to the complementarities in age parameter. The affinity matrix estimate corresponding to age is the biggest in magnitude. Therefore, this counterfactual is equivalent to simulating a marriage market with an increase in complementarities in height. Figures A8, A9, A10, A11 and A12 show the results across religion-caste-specific marriage markets. The figures show a substantial increase in positive assortative matching on height. Overall, the results from the two counterfactuals illustrate the role of preferences for height in the marriage market in determining marital sorting on height.

6.2 Complementarity in Height Unchanged Over Time

Given the heterogeneous changes in complementarity in height across religion-caste-specific marriage markets as described in the previous section, I estimate couples' counterfactual joint height distribution if preferences for height had remained unchanged over time. More precisely, I impose the height comple-

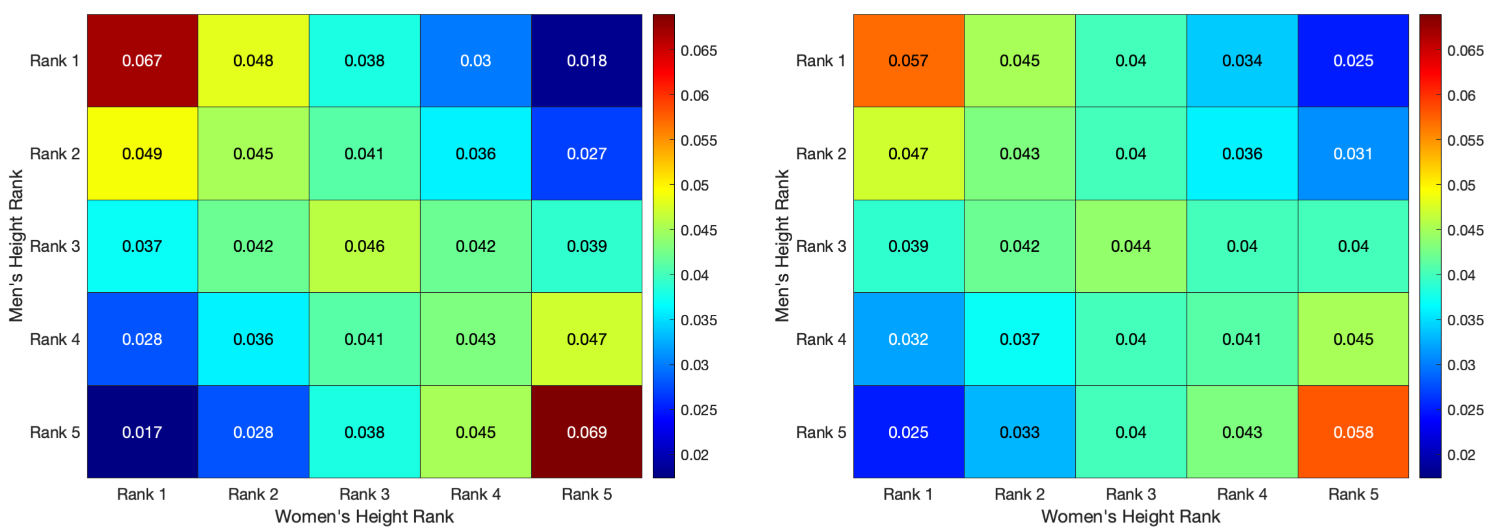
Figure 4: Joint Height Distribution (Other Backward Caste): Complementarity Unchanged Over Time



(A) 1970-1980 Preferences (Actual) (B) 1950-1960 Preferences (Counterfactual)

Note: Figure (A) shows the actual rank-rank matching for the Other Backward Caste couples belonging to the young cohort. Figure (B) indicates the counterfactual rank-rank matching for couples belonging to the young cohort by imposing the complementarity in height parameter corresponding to the old cohort. Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile.

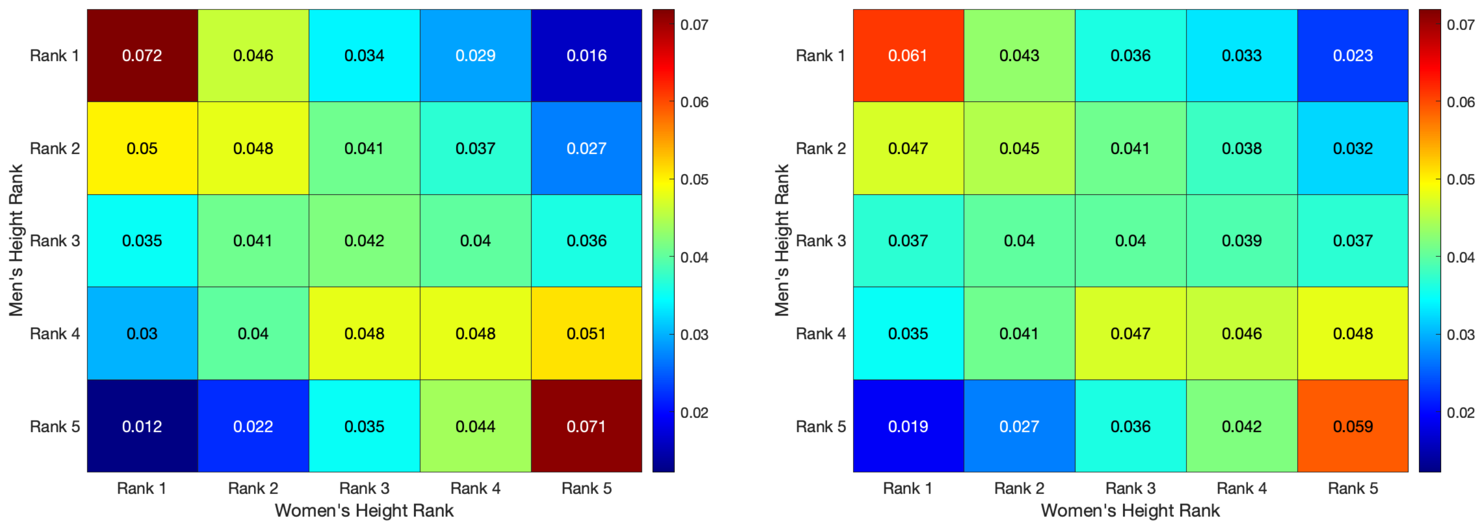
Figure 5: Joint Height Distribution (Scheduled Tribe): Complementarity Unchanged Over Time



(A) 1970-1980 Preferences (Actual) (B) 1950-1960 Preferences (Counterfactual)

Note: Figure (A) shows the actual rank-rank matching for the Scheduled Tribe couples belonging to the young cohort. Figure (B) indicates the counterfactual rank-rank matching for couples belonging to the young cohort by imposing the complementarity in height parameter corresponding to the old cohort. Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile.

Figure 6: Joint Height Distribution (Muslims): Complementarity Unchanged Over Time



(A) 1970-1980 Preferences (Actual) (B) 1950-1960 Preferences (Counterfactual)

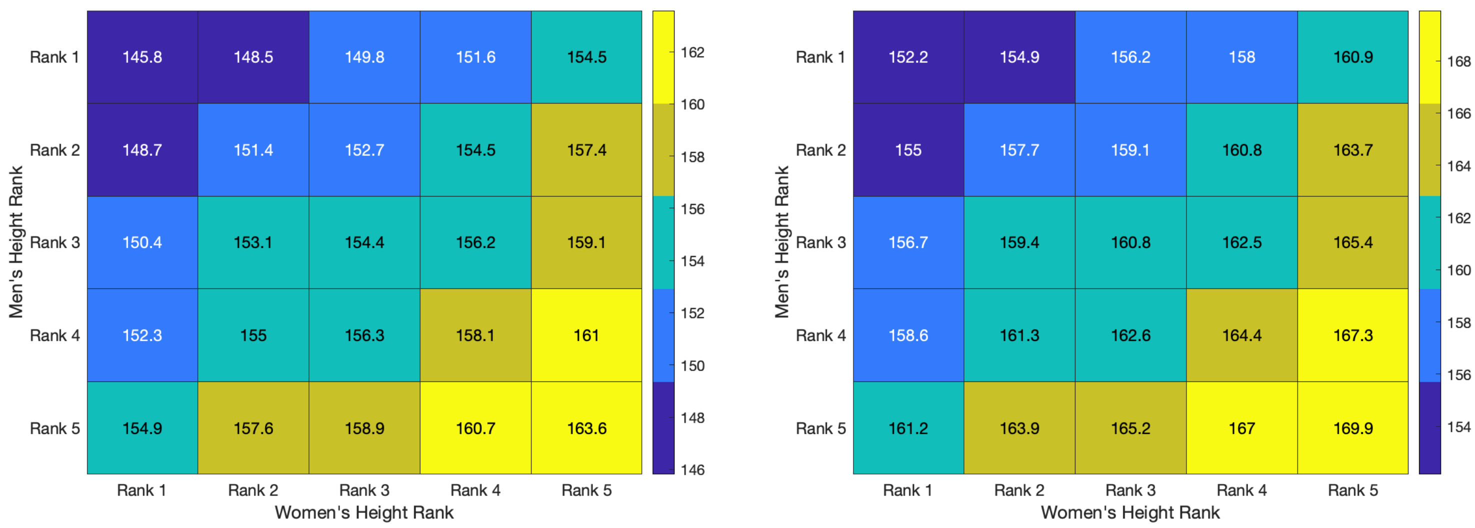
Note: Figure (A) shows the actual rank-rank matching for the Muslim couples belonging to the young cohort. Figure (B) indicates the counterfactual rank-rank matching for couples belonging to the young cohort by imposing the complementarity in height parameter corresponding to the old cohort. Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile.

mentarity parameter of the old cohort onto the young cohort's affinity matrix, keeping all other elements unchanged, and estimate the counterfactual joint height distribution. Similar to the previous counterfactual simulation, I divide men and women into five height ranks and compare the actual rank-rank matching on height for the young cohort to the counterfactual rank-rank matching by imposing the complementarities in the height of the old cohort. Figure 4 shows the results for the Other Backward Caste marriage market. From Table 7, complementarity in height has increased only marginally, and this is reflected in the results of the counterfactual simulation. The joint height distribution of couples belonging to the young cohort shows relatively no change when we impose the height preferences of the old cohort. The probability of a height rank-one man marrying a height rank-one woman and a rank five-man marrying a rank five-woman remains constant at around 6%. Similarly, the likelihood of a height rank-one man marrying a height rank- five woman and vice-versa remains stable at around 2%. Therefore we do not see a substantial change in the degree of assortative matching when the complementarity in the height of the old cohort is imposed on the young cohort for the Other Backward Caste couples.

From Table 7, the Scheduled Tribe and the Muslim couples show the largest increase in complementarity on height over time. Figure 5 and Figure 6 show the results from the counterfactual simulation for these two groups, the counterfactual rank-rank matching indicates that the probability of a height rank-one man marrying a height rank-one woman and a height rank five-man marrying a height rank five-woman falls by one percentage point. Similarly, we see an increase in the likelihood of a height rank-one man marrying a height rank- five woman and vice-versa. The counterfactual simulation indicates that the degree of positive assortative matching on height decreases when the complementarity in height parameter of the older cohort is imposed on the young cohort for the Scheduled Tribe and Muslim couples. As the results in Table 7 show that the change in complementarity in height over time for the the Upper Caste and Scheduled Caste group is negligible, for these two groups we do not see a substantial change in the degree of assortative matching when the complementarity in the height of the old cohort is imposed on the young cohort (results not shown, but available upon request).

6.3 Children's Potential Height Distribution

Figure 7: Children's Potential Height: Other Backward Caste

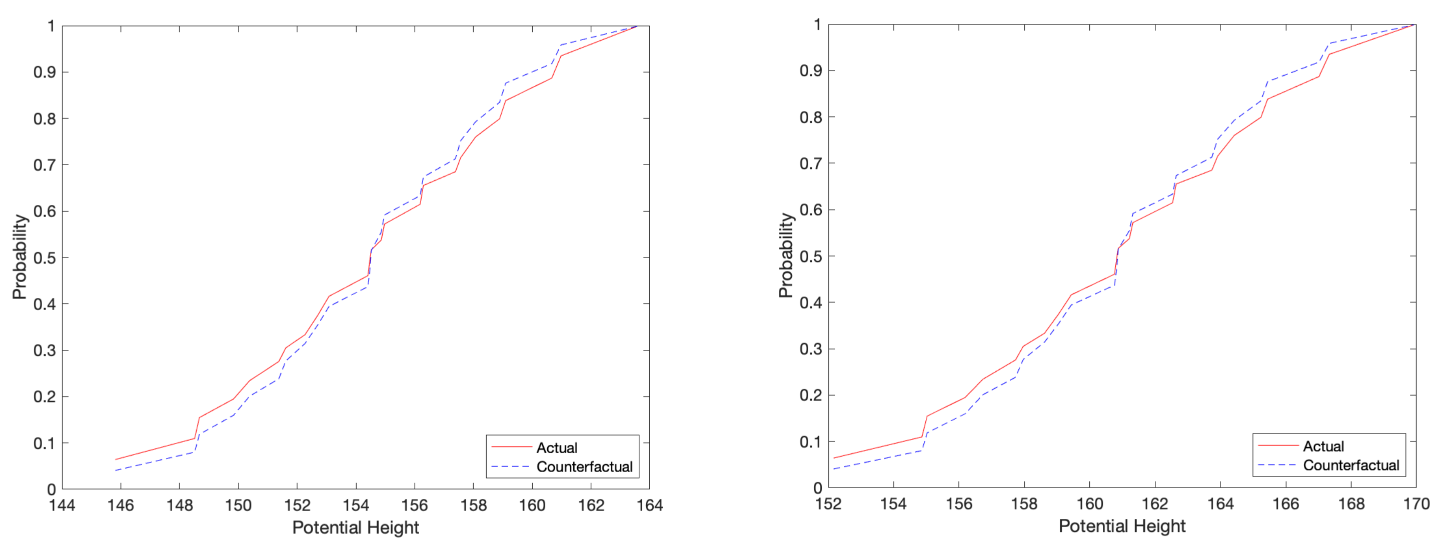


(A) Girl's Potential Height

(B) Boy's Potential Height

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970).

Figure 8: Children's Potential Height Distribution (Other Backward Caste): Actual vs Counterfactual



(A) Girl's Potential Distribution

(B) Boy's Potential Distribution

Note: Figure (A) shows girl's potential height with respect to parental height rank and Figure (B) shows boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970). Counterfactual refers to the hypothetical scenario with no complementarity in height in the marriage market.

Height is a polygenic trait that depends on both genetic and environmental factors. The medical literature suggests that height is a highly heritable trait, with around 80% of the variation in height explained by genetics (Stulp and Barrett, 2016). Pediatricians dating back to the 1800s have calculated a child's target height as a function of parental height. The earliest example of this is the work of Galton (1886) who argued that mid-parental height (average of the mother's and father's height) best represents the transmission of stature from parents to children. Mid-parental height is still considered a strong predictor of children's adult height (Cole, 2000). A modification to mid-parental height by sex introduced by Tanner et al. (1970), known as Tanner's method, is a popular technique used by pediatricians today to predict a child's height potential. According to the Tanner's method, son's target height or potential height is given by:

$$\frac{(\text{Father Height} + \text{Mother Height})}{2} + 6.5 \text{ centimeters},$$

and a daughter's target height is given by:

$$\frac{(\text{Father Height} + \text{Mother Height})}{2} - 6.5 \text{ centimeters},$$

where 6.5 centimeters is the gender correction factor, calculated as the difference in the boy's average height and the girl's average height.[34] A crucial caveat in developing countries like India is that Tanner's method can underestimate a child's height potential (Atluri, Bharathidasan, and Sarathi, 2018). However, even in India, mid-parental height plays a vital role in predicting a child's adult height; according to the WHO Multicentre Growth Reference Study (Garza et al., 2013), mid-parental height explains about 21% of the variability in linear growth from birth to 2 years of children in India.

Figure 7 shows the potential height distribution for the children of Other Backward Caste couples by individual height rank calculated using Tanner's method.[35] The average potential height for a girl (boy) with height rank-one father and height rank-one mother is 164 (170) centimeters. In contrast, the average potential height of a girl (boy) with height rank-five father and height rank-five mother is 146 (152) centimeters.

Next, I analyze the impact of changes in the preferences for height in the marriage market on the girl's and boy's potential height distribution. I simulate a hypothetical marriage market with no complementarity in height in the marriage market and compute the potential height cumulative distribution for boys and girls. Figure 8 shows the results from this counterfactual simulation for the Other Backward Caste couples. The results indicate that preferences for height in the marriage market impact the distribution of children's potential height. Although the average potential height of boys and girls remains unchanged, we see a shift in the distribution, such that the prevalence of short and tall children decreases. For example, from Figure 8(A), under the actual equilibrium matching, the probability that a girl's target height is less than 150 centimeters is 20%; this probability falls to 16% when there are no complementarities in height in the marriage market. Similarly, the probability that a girl's target height is greater than 160 centimeters falls by 4 percentage points. The standard deviation of girls' potential height distribution decreases by four percent in the hypothetical marriage market with no complementarity in height. An analogous result is observed for boys potential height in Figure 8(B), where the probability that a boy's target height is less than 155 centimeters, as well as the probability that a boy's target height is greater than 165 centimeters, decreases by 4 percentage points. The standard deviation of boys' potential height distribution decreases by four percent in the hypothetical marriage market with no complementarity in height. Overall, this implies that the inequality in potential height decreases as the complementarity in height in the marriage market decreases. The results for other religion-caste groups, shown in the appendix figures A14, A16, A18 and A20 are qualitatively similar.

To further illustrate the impact of complementarity in height on the potential height distribution, I

[34]There are several modified versions of Tanner's method, each designed to improve the accuracy of the potential height measure, I do not go into the details of various adjustments to Tanner's method (see Cole (2000) for details), as it's beyond the scope of the paper. I use the original version's of Tanner's method for my analysis.

[35]Figures A13, A15, A17 and A19 show the potential distribution for the remaining religion-caste groups

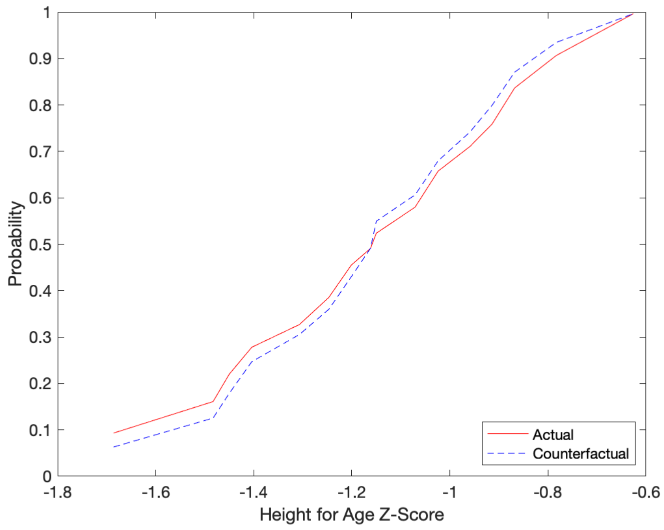
simulate an alternate counterfactual, wherein I set the complementarity in height parameter equal to the complementarity in age and compute the hypothetical potential height distribution. Figure A21 compares the actual potential height distribution versus the counterfactual potential height distribution for boys whereas Figure A22 shows the results for girls. We once again see significant distributional effects; as complementarity in height increases, the likelihood of children with small height goes up but so does the likelihood of children with tall height. The standard deviation of the potential height distribution under the counterfactual preferences goes up by approximately 8%, which indicates a substantial increase in the height inequality within the religion-caste group. In conclusion, the counterfactual simulation illustrates the role of complementarities in height in the marriage market in one generation on the next generation's height distribution. It provides one possible channel through which inequality in height could propagate over time.

6.4 Children's Height-for-Age

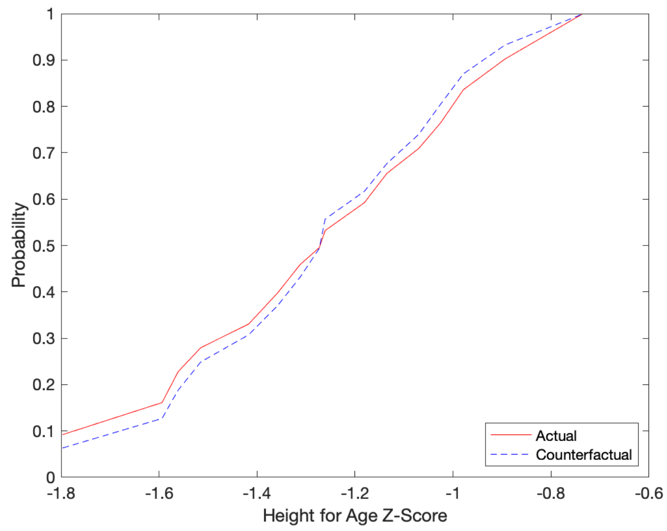
To further assess the impact of preferences for height in the marriage market on children's stunting hazard, I compare children's height for age z-score distribution under various hypothetical preferences for height to the actual distribution. The analysis involves two steps. In the first step, I run a linear regression of parental height rank on children's height for age z-score, conditional on parental education, parental age, household expenditure, whether the household has piped water, the mother's parent's literacy, the father's parent's literacy, child's gender, along with district fixed effects, religion-caste group fixed effects and age fixed effects. Using the estimates from the regression, I obtain predicted height for age z-score conditional on other parental characteristics and household-level variables for every combination of parental height rank. In the second step, I compute the occurrence of every rank-rank matching under the actual preferences for height and the hypothetical preferences (no complementarity in height in the marriage market). This gives me the final distribution of children's height for age z-score under the actual and hypothetical preferences for height.

Figure 9 shows the impact of complementarities in height in the marriage market on children's height-for-age cumulative distribution across religion-caste groups. From Figure 9, although complementarities in height in the marriage market do not impact the average height-for-age, they significantly impact the children's height for age z-score distribution. Under the hypothetical preferences, with no complementarity in height in the marriage market, we find that the standard deviation of the height for age z-score distribution decreases across religion-caste groups by 3 percent. The shift in the cumulative distribution function under the counterfactual reduces the likelihood of children with small height-for-age, as well as the likelihood of tall children. In particular, for the Scheduled Tribe group, we find that the complementarity in height in the marriage market can increase the prevalence of stunting in children by 4 percentage points. To assess the magnitude of the coefficient, Jayachandran and Pande (2017) find that due to strong eldest son preference in India, relative to their African counterparts, the stunting hazard is 5 percentage points and 6 percentage points higher for second birth order and third birth order children compared to their oldest sibling, respectively.

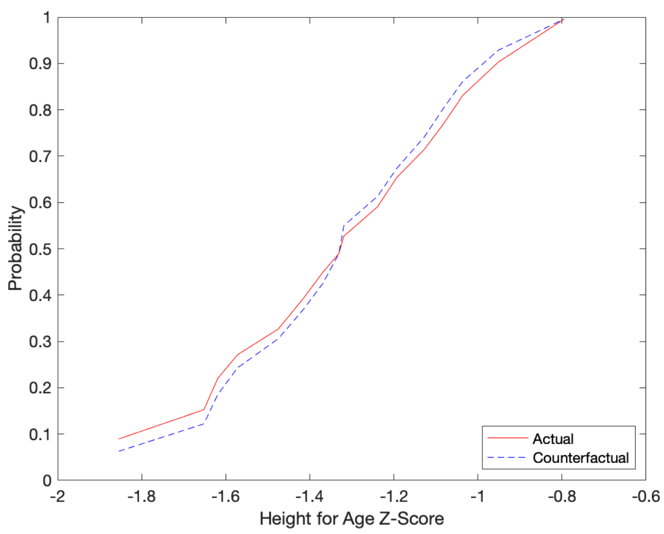
Figure 9: Children's Height For Age Z-Score Distribution: Actual vs Counterfactual



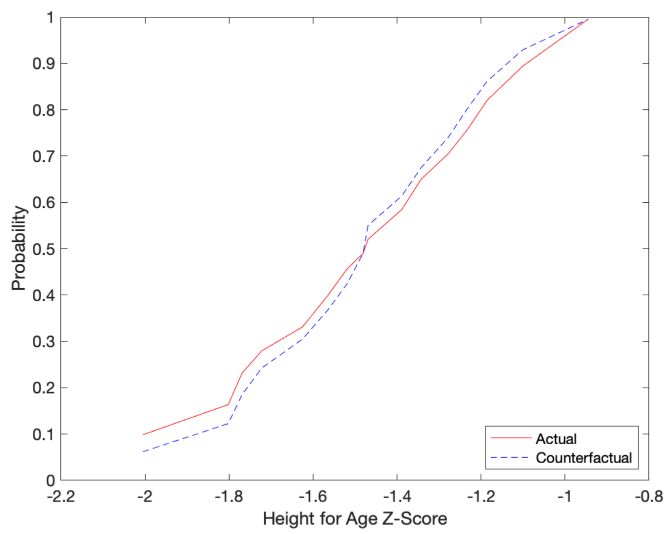
(A) Upper Caste



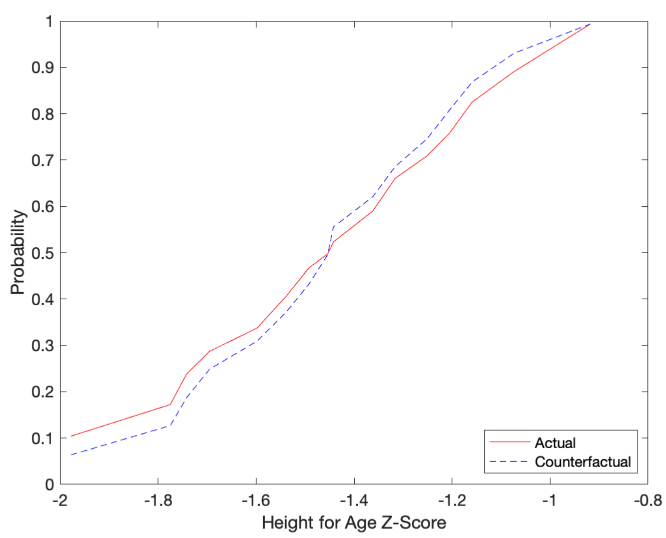
(B) Other Backward Caste



(B) Scheduled Caste



(B) Scheduled Tribe



(B) Muslims

Note: X-axis is the predicted height for age z-score. Counterfactual preferences refer to the hypothetical scenario, in which there are no complementarities in height in the marriage market. Height for age z-score calculated for children between the age of 0 and 19 using the WHO Child Growth Charts.

7 Conclusion

Height plays a crucial role in determining who marries whom in India. Given the vital link between parental height and children's height and the long-term impacts of height on individual well-being, this paper structurally estimates preferences for height in the Indian marriage market and studies the influence of marital preferences for height on children's height distribution.

Using detailed data on the husband and the wife's individual and family characteristics, I estimate a two-sided transferable utility model of the marriage market utilizing the framework of Dupuy and Galichon (2014). I find strong complementarity in men's and women's height across religion-caste groups. For the majority of the religion-caste groups, I also find cross-complementarity in men's education and women's height. Next, I analyze the changes in matching and sorting patterns in height over time. I find a mild increase in complementarity in height with substantial heterogeneity across religion-caste groups.

Using the model estimates, I simulate hypothetical marriage markets with counterfactual preferences for height and compute children's potential height (growth potential) as a function of parental height using a well-known procedure from the medical literature known as Tanner's method (Tanner et al., 1970). Results from the counterfactual simulation suggest that complementarity in height significantly impacts children's potential height distribution. In particular, I find that complementarity in height in the marriage market can increase the standard deviation of children's potential height distribution by 3%, indicating an increase in height inequality among children. Similarly, complementarity in height in the marriage market can impact children's height-for-age distribution and increase the stunting hazard by up to 4 percentage points. This effect is comparable to the impact of strong son eldest preference on stunting among lower birth order children in India (Jayachandran and Pande, 2017).

There are several directions along which this paper can be expanded; first, the current framework allows me to estimate complementarity in height but does not allow me to estimate preferences concerning height for men and women separately. This could be achieved using a survey design as in Chiappori et al. (2021) to estimate the willingness to pay for height in terms of family income for men and women separately. Second, to explicitly include marital payments, dowries into the framework and study the relationship between dowries and height. In particular, answering the following question: What is the marriage market premium in terms of dowry received for men with respect to height? Future research will attempt to answer these questions.

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A Appendix

Contents

A.1 Singular Value Decomposition of the Affinity Matrix

The affinity matrix helps us understand the degree of complementarity/ substitutability between these features. Next, we would like to quantify the relative importance of each of these features in explaining the marital surplus. This is achieved using a technique advocated by Dupuy and Galichon (2014) known as saliency analysis. This technique has been used by Ciscato, Galichon, and Goussé (2020) to compare the relative importance of education, age, and wages across the heterosexual, gay, and lesbian marriage markets in the United States and by Chiappori et al. (2020a) to study the relative importance of education, anthropometric measures, and health-related risk behaviors in the marriage market using data from Italy. Here I summarize the saliency analysis technique for my particular application.

The technique involves expressing the original joint utility function,$\Phi(x, y)$, in-terms of orthogonal vectors, $\tilde{x}$ and $\tilde{y}$, such that $\Phi(x, y) = x^T Ay = \tilde{x}^T \Lambda \tilde{y}$, where, Λ is a diagonal matrix. If λ_i is the i^{th} diagonal entry of matrix Λ, then $\frac{\lambda_i}{\sum_i \lambda_i}$ is the proportion of the joint utility explained by the i^{th} pair of the orthogonal vectors, $\tilde{x}$ and $\tilde{y}$. Each element of $\tilde{x}$ and $\tilde{y}$ is a weighted sum of the underlying attributes, namely, age, education, height, and parental education. By analyzing the loading weights of the underlying observables on the independent vectors, we can quantify the relative importance of each of the martial features in explaining the joint utility separately for men and women. This sheds light on questions such as: How much of the joint marital utility is explained by height independently? and what is the relative importance of height in explaining the marital surplus compared to education?

The fundamental technique used is the singular value decomposition (SVD) of the affinity matrix A.[36] Using SVD, we can rewrite A as $U^T \Lambda V$, therefore the orthogonal vectors $\tilde{x}$ and $\tilde{y}$ previously defined can be written as, $\tilde{x} = Ux$ and $\tilde{y} = Vy$.

After estimating the affinity matrix using equation 5, I perform SVD on the estimated affinity matrix for each caste-religion-specific marriage market and quantify the relative importance of education, height, and parental education for men and women in each of the religion-caste-specific marriage markets.

A.2 Derivation: Relationship Between Equilibrium Matching and Joint Utility

Dupuy and Galichon (2014) show that by assuming partners are drawn randomly from a Poisson process leads to a continuous multinomial logit choice model. Therefore, the probability of a man with feature vector x, choosing a woman with feature vector y from his randomly drawn set is given by,

$$\pi(y|x) = \frac{e^{[U(x,y)/(\sigma/2)]}}{\int_{\mathbb{R}^4} e^{[U(x,t)/(\sigma/2)]} dt}. \tag{A1}$$

[36] Before performing SVD, we rescale the the observable vectors, X and Y, so that each element of X and Y is mean zero and has a variance of one.

Similarly, the probability of a woman, w with a feature vector y choosing a man with feature vector x from her randomly drawn set is given by,

$$\pi(x|y) = \frac{e^{[V(t,y)/(\sigma/2)]}}{\int_{\mathbb{R}^4} e^{[V(t,y)/(\sigma/2)]} dt}. \tag{A2}$$

Since, $\pi(y|x) = \pi(x, y)/f_x(x)$ and $\pi(x|y) = \pi(x, y)/f_y(y)$. we can write the following equality:

$$\pi(x, y) = \frac{e^{[V(t,y)/(\sigma/2)]}}{\frac{\int_{\mathbb{R}^4} e^{[V(t,y)/(\sigma/2)]} dt}{f_y(y)}} = \frac{e^{[U(x,y)/(\sigma/2)]}}{\frac{\int_{\mathbb{R}^4} e^{[U(x,t)/(\sigma/2)]} dt}{f_x(x)}}.$$

Therefore, we have $(\sigma/2)\log(\pi(x, y)) = V - b(y) = U - a(x)$, where,

$$b(y) = \sigma/2 \times \log\left(\frac{\int_{\mathbb{R}^4} e^{[V(t,y)/(\sigma/2)]dt}}{f_y(y)}\right),$$

$$a(x) = \sigma/2 \times \log\left(\frac{\int_{\mathbb{R}^4} e^{[U(t,y)/(\sigma/2)]} dt}{f_x(x)}\right),$$

which implies that $\log(\pi(x, y)) = U + V - a(x) - b(y)$. Since, $\Phi(x, y) = U + V$, we obtain the final expressions as follows:

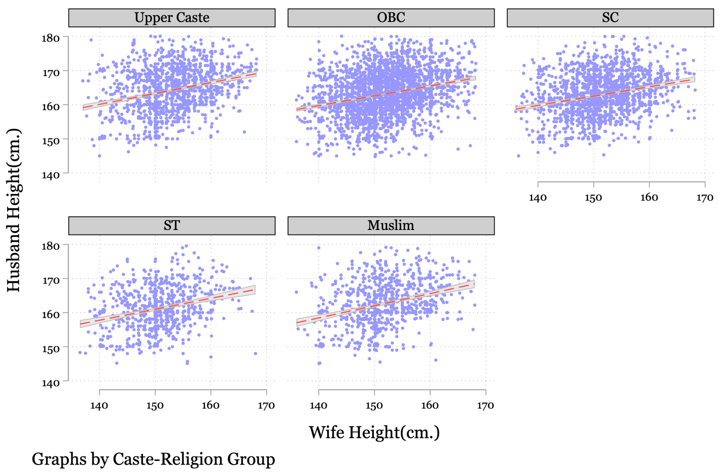
$$\log \pi(x, y) = \frac{\Phi(x, y) - a(x) - b(y)}{\sigma},$$

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

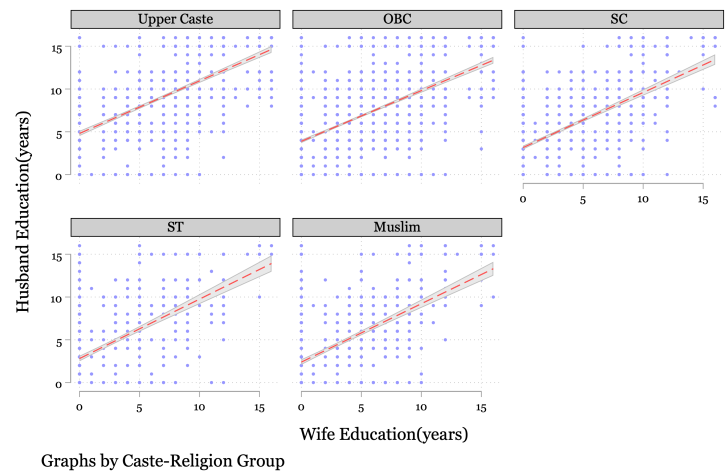
$$V = \frac{\Phi(x, y) - a(x) + b(y)}{2}.$$

A.3 Figures and Tables

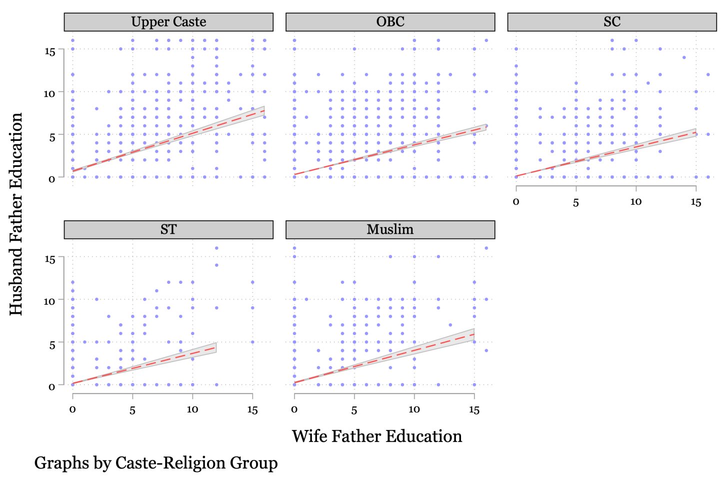
Figure A1: Correlations Between Husband and Wife Marriage Market Features



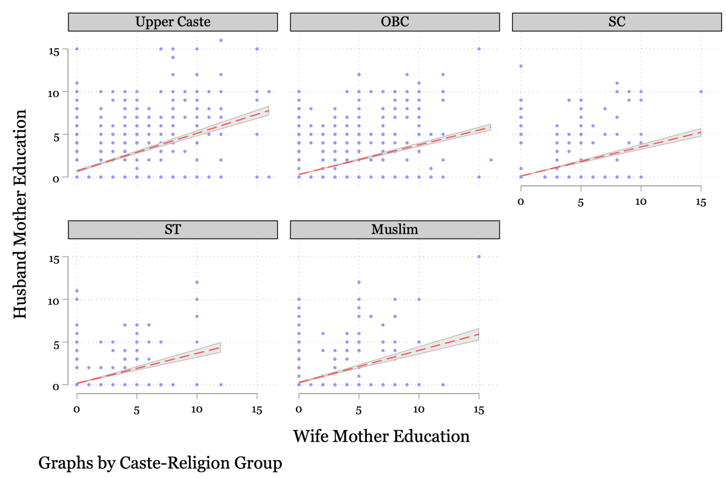
(A) Height



(B) Education



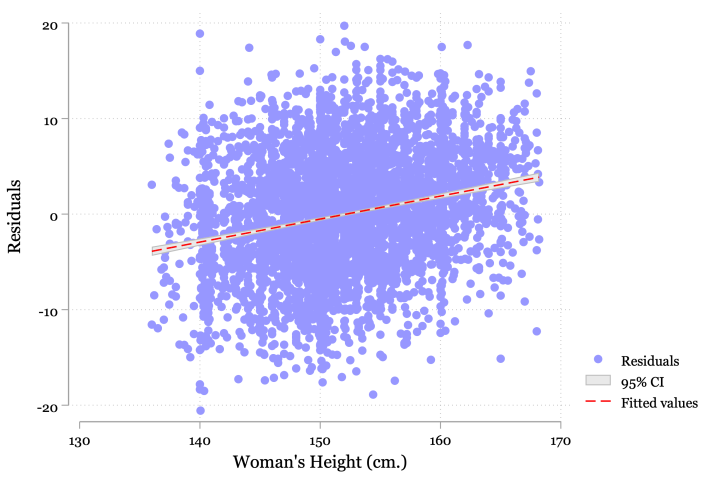
(C) Father Education



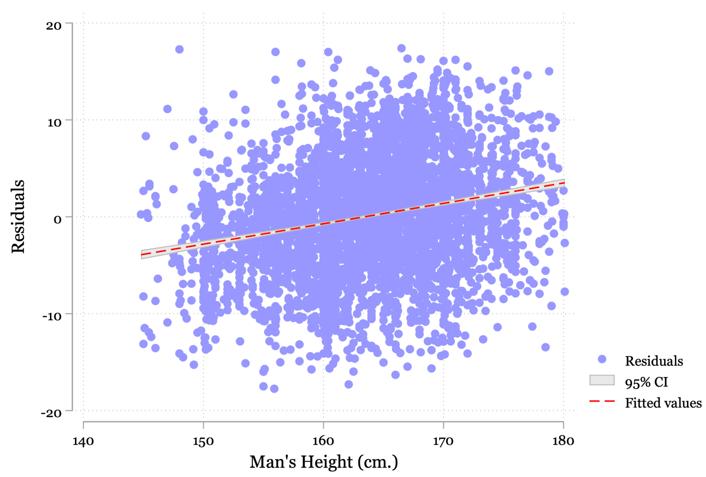
(C) Mother Education

Note: Figure shows the correlations between the husband and the wife's marriage market features using the IHDS sample

Figure A2: Height Regression: Residuals



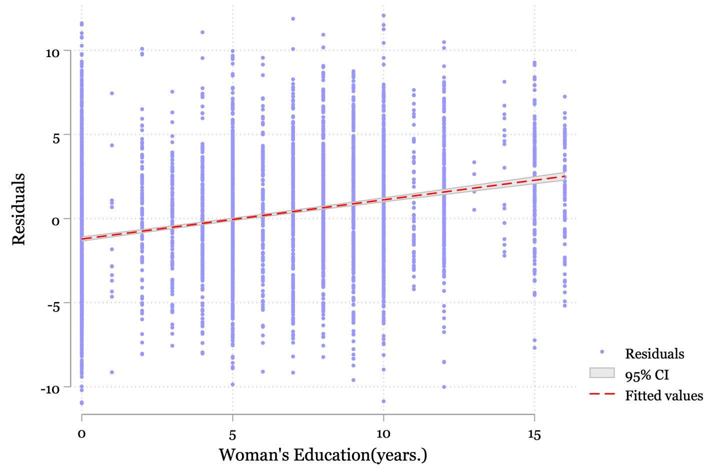
(A) Men's Height
Regression Residuals



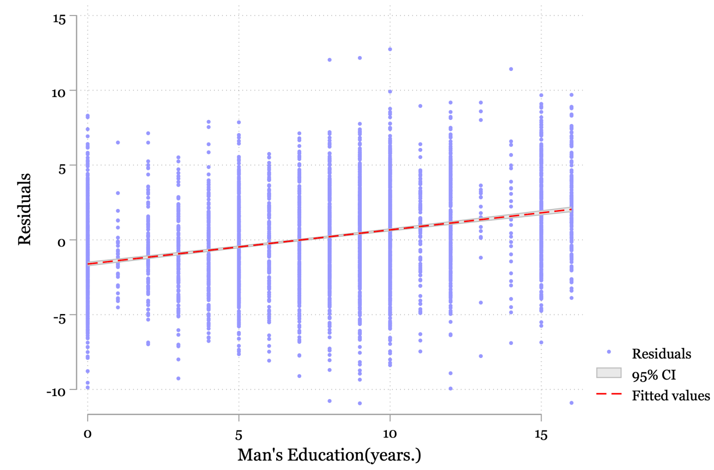
(B) Women's Height
Regression Residuals

Note: Figure (A) shows the residuals obtained after regressing men's height on observables excluding women's height. Figure (B) shows the residuals obtained after regressing women's height on observables excluding men's height. Observables include: the husband and the wife's education, father's education, mother's education, year of marriage fixed effects, state fixed effects and caste-religious group fixed effects, with standard errors clustered at the state-level.

Figure A3: Education Regression: Residuals



(A) Men's Education Regression Residuals

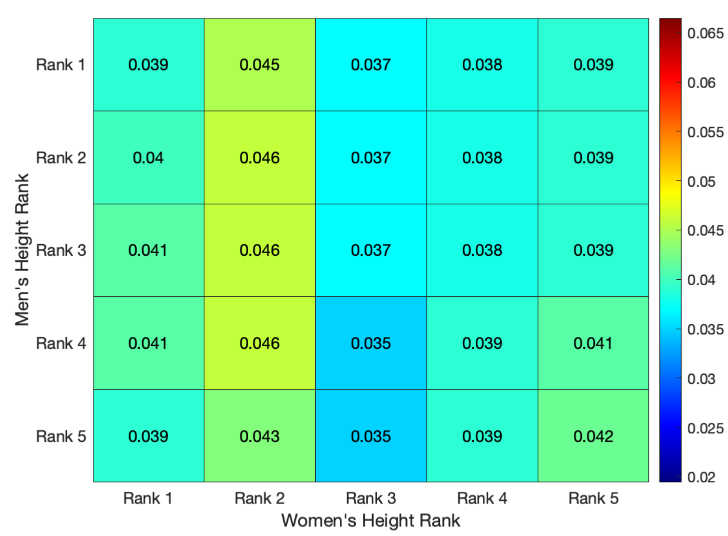


(B) Women's Education Regression Residuals

Note: Figure (A) shows the residuals obtained after regressing men's education on observables excluding women's education. Figure (B) shows the residuals obtained after regressing women's education on observables excluding men's education. Observables include: the husband and the wife's education, father's education, mother's education, year of marriage fixed effects, state fixed effects and caste-religious group fixed effects, with standard errors clustered at the state-level.

Figure A4: Matching on Height (Upper Caste): No Complementarity in Height

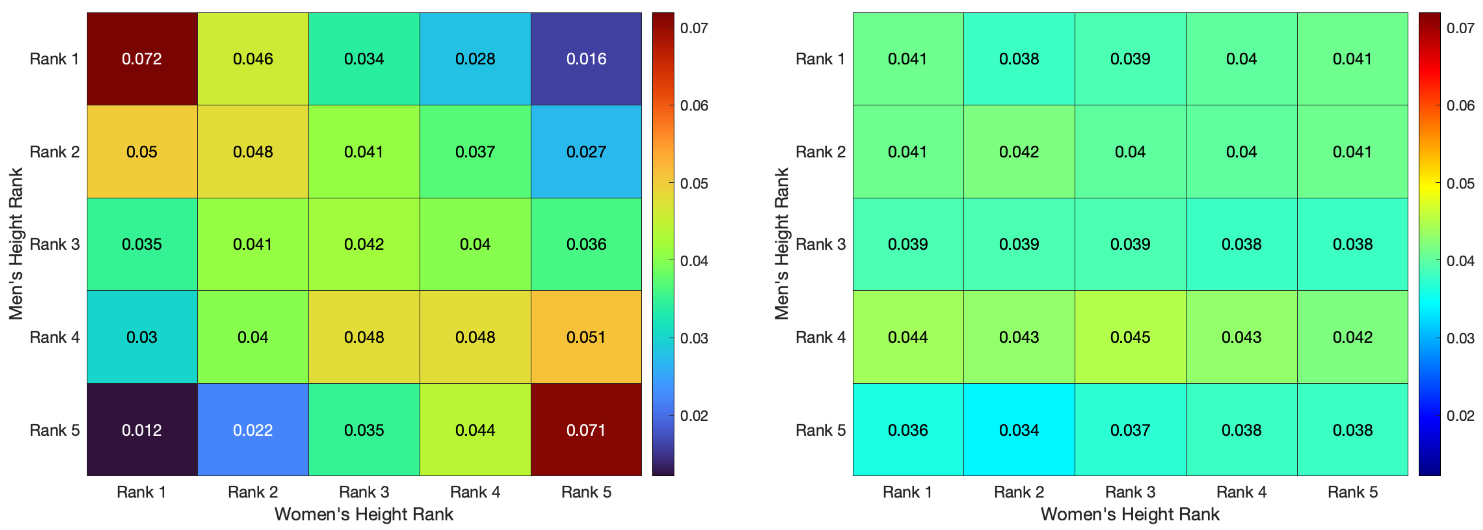
(A) Predicted Rank-Rank Matching



(B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if there was no complementarity in height in the marriage market. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

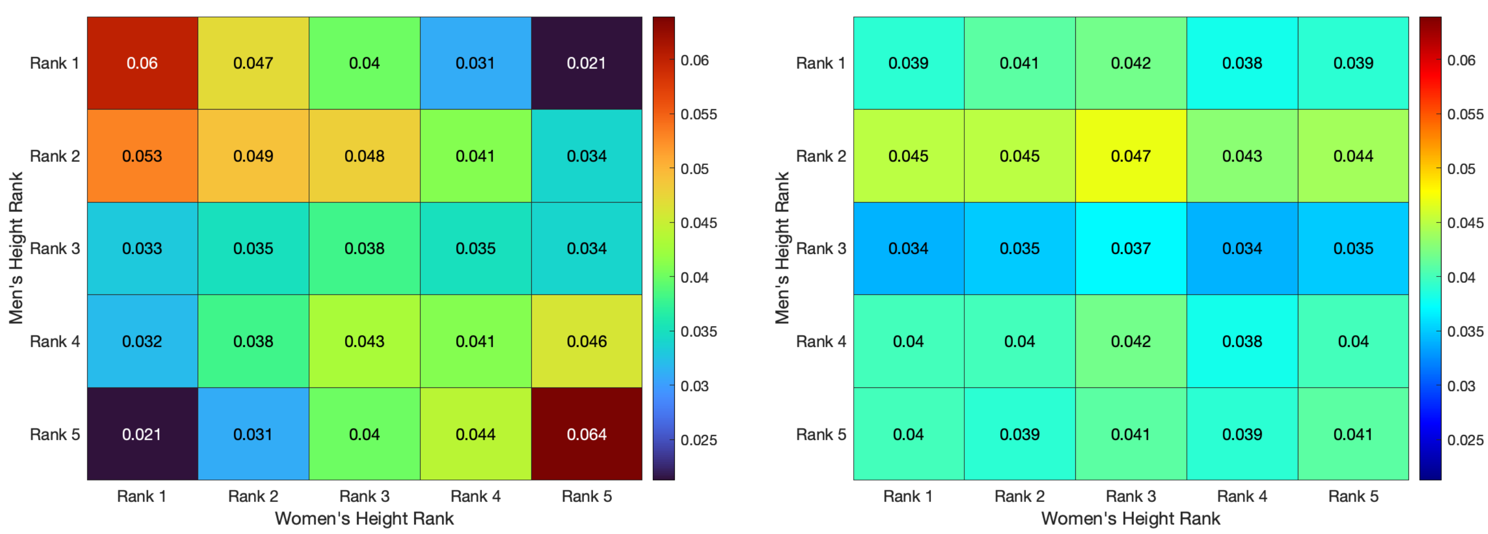
Figure A5: Matching on Height (Muslims): No Complementarity in Height



(A) Predicted Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if there was no complementarity in height in the marriage market. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

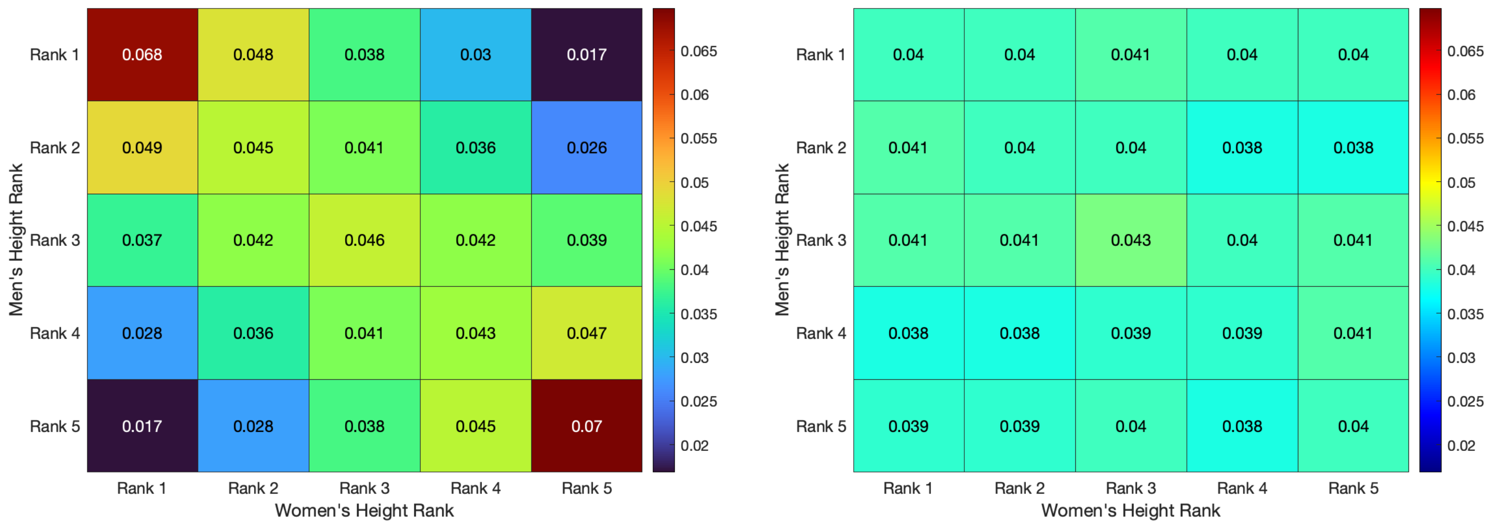
Figure A6: Matching on Height (Scheduled Caste): No Complementarity in Height



(A) Predicted Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if there was no complementarity in height in the marriage market. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

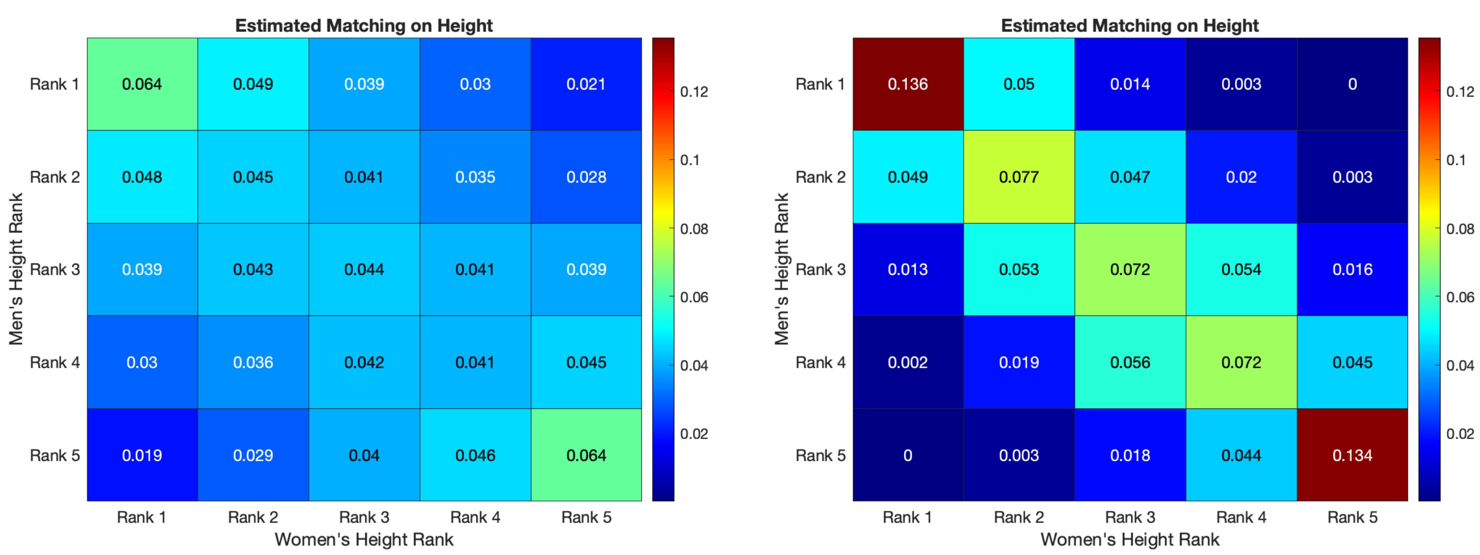
Figure A7: Matching on Height (Scheduled Tribe): No Complementarity in Height



(A) Predicted Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if there was no complementarity in height in the marriage market. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

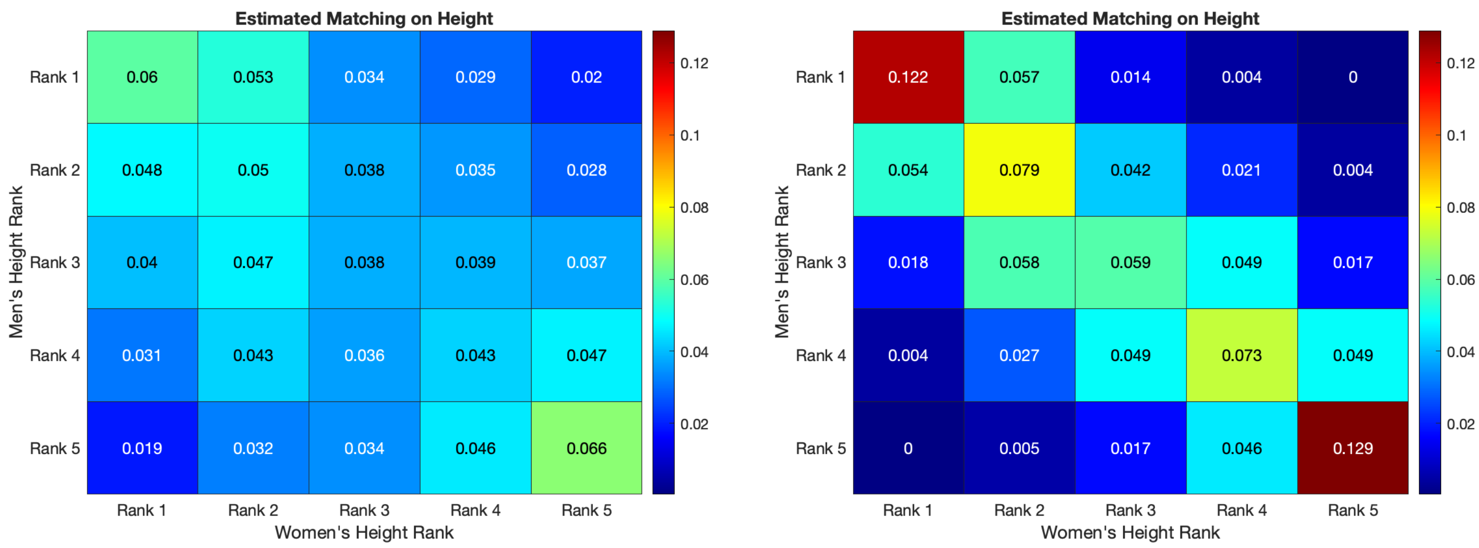
Figure A8: Matching on Height (Other Backward Caste): Same Complementarity as Age



(A) Actual Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if the complementarity in height in the marriage market was the same as the complementarity in age. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

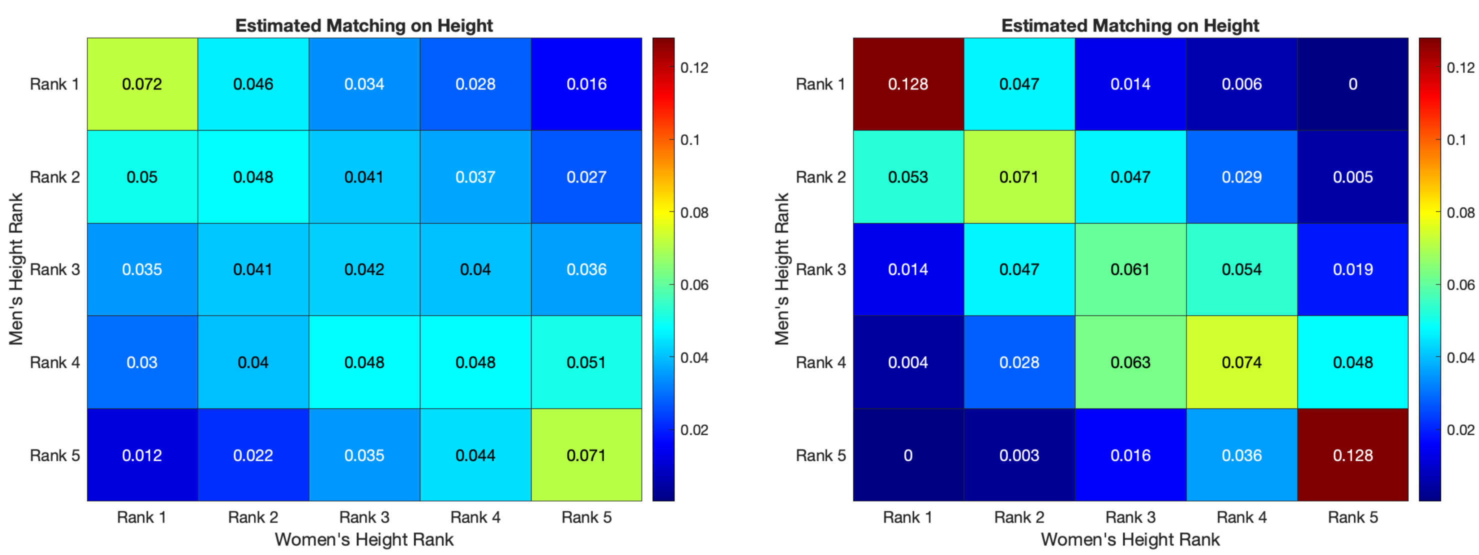
Figure A9: Matching on Height (Upper Caste): Same Complementarity as Age



(A) Actual Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if the complementarity in height in the marriage market was the same as the complementarity in age. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

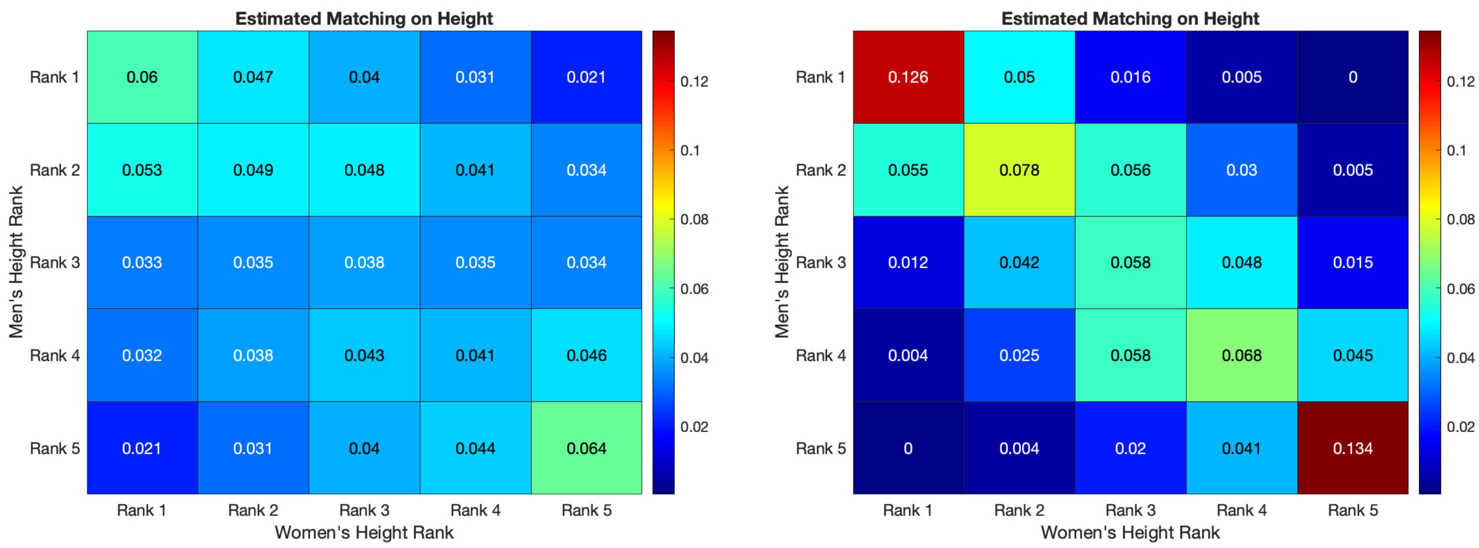
Figure A10: Matching on Height (Muslims): Same Complementarity as Age



(A) Actual Rank-Rank Matching (B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if the complementarity in height in the marriage market was the same as the complementarity in age. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

Figure A11: Matching on Height (Scheduled Caste): Same Complementarity as Age

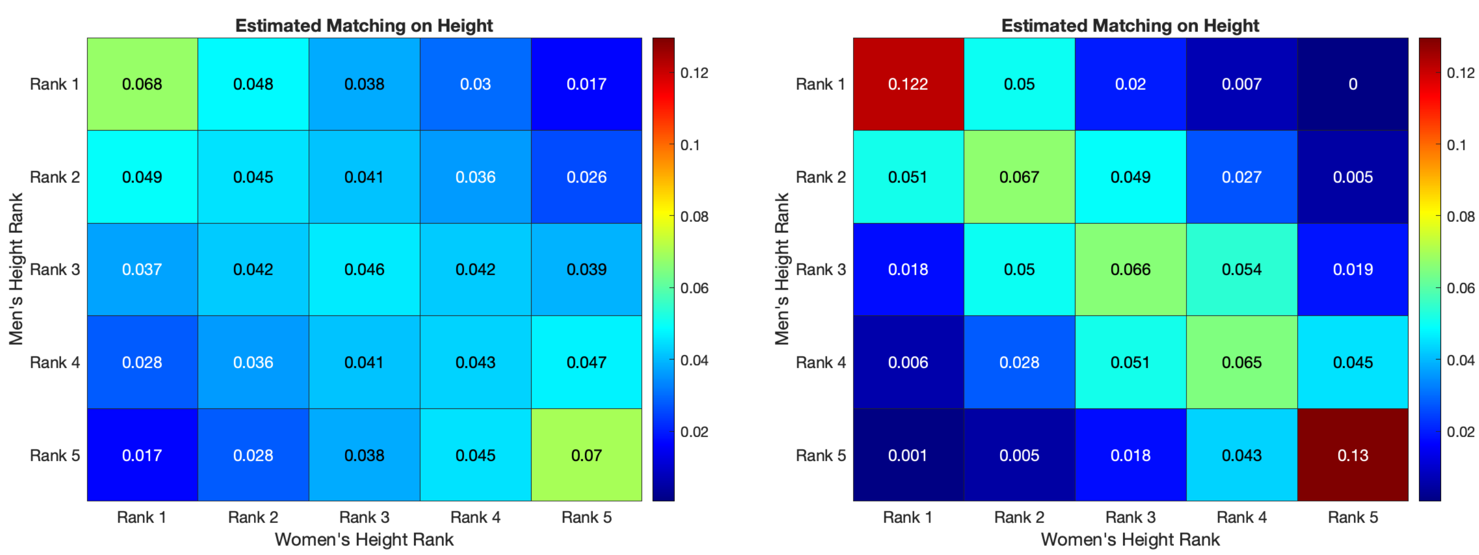


(A) Actual Rank-Rank Matching

(B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if the complementarity in height in the marriage market was the same as the complementarity in age. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

Figure A12: Matching on Height (Scheduled Tribe): Same Complementarity as Age

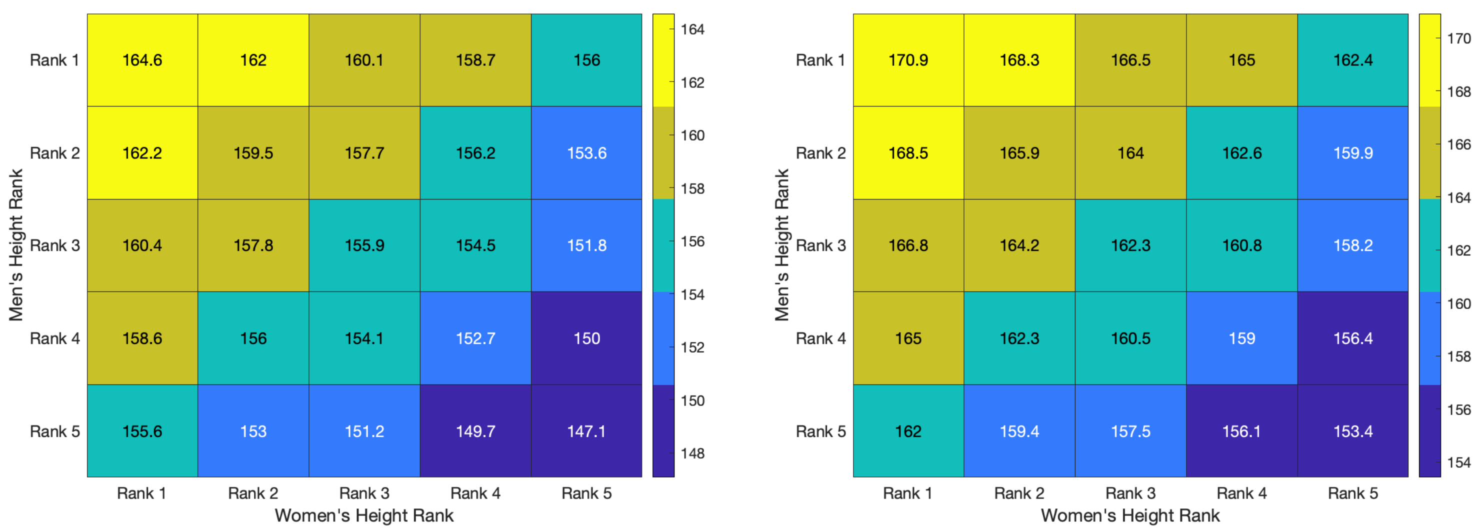


(A) Actual Rank-Rank Matching

(B) Counterfactual Rank-Rank Matching

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the actual Rank-Rank matching and Figure (B) shows the counterfactual Rank-Rank matching if the complementarity in height in the marriage market was the same as the complementarity in age. Each value represents the probability mass of a given rank-rank matching. The entries sum to one.

Figure A13: Children's Potential Height: Upper Caste

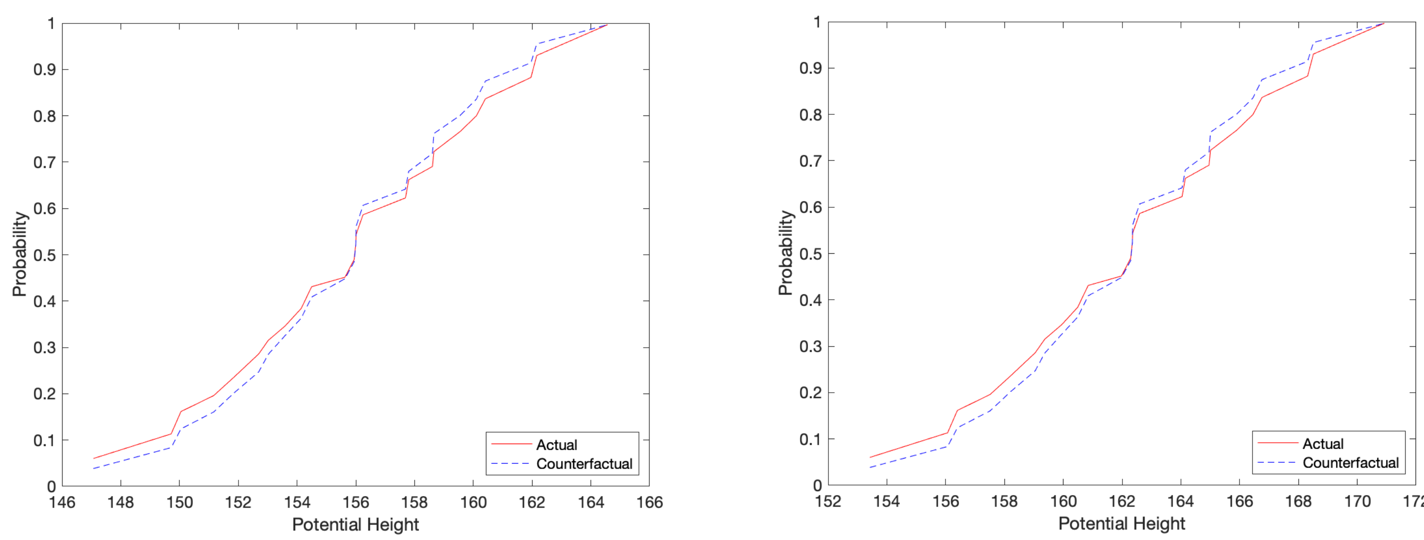


(A) Girl's Potential Height

(B) Boy's Potential Height

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970).

Figure A14: Children's Potential Height Distribution (Upper Caste): Actual vs Counterfactual

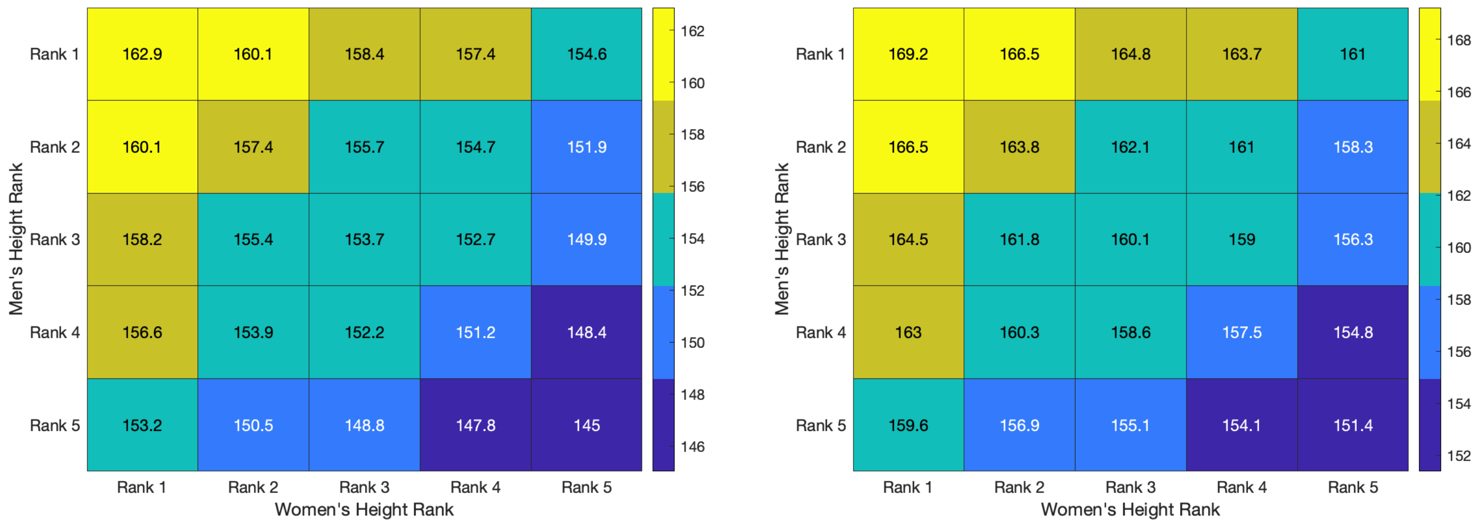


(A) Girl's Potential Distribution

(B) Boy's Potential Distribution

Note: Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970). Counterfactual potential height distribution is calculated under the hypothetical, no complementarity in height in the marriage market.

Figure A15: Children's Potential Height: Muslims

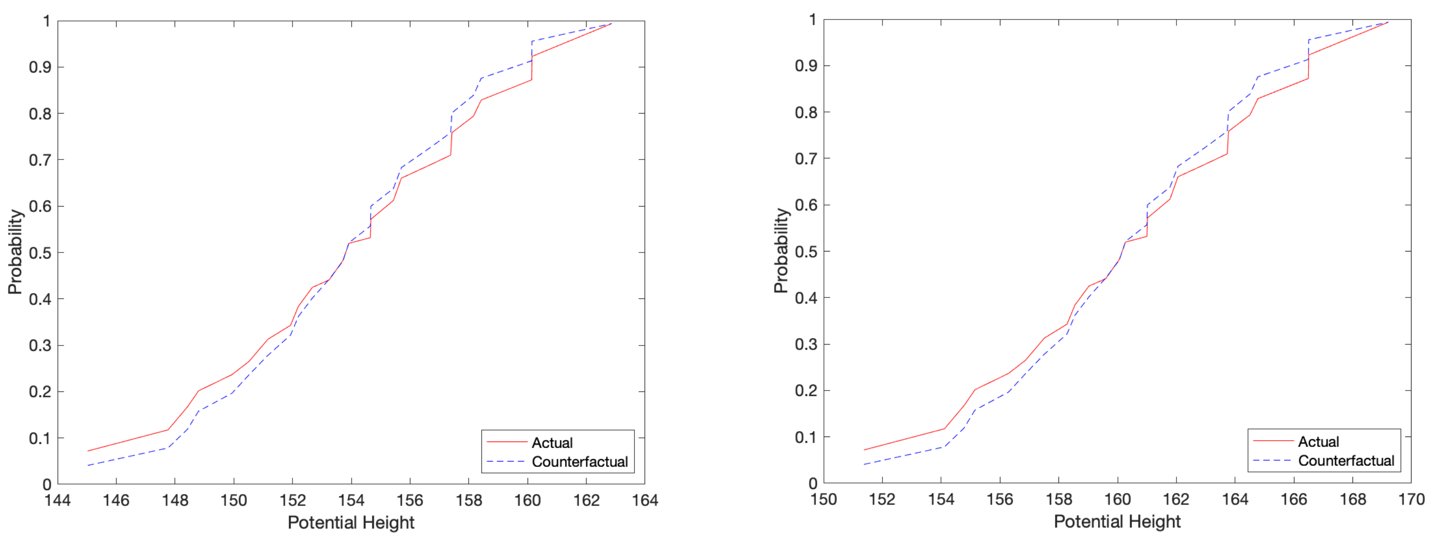


(A) Girl's Potential Height

(B) Boy's Potential Height

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970).

Figure A16: Children's Potential Height Distribution (Muslims): Actual vs Counterfactual

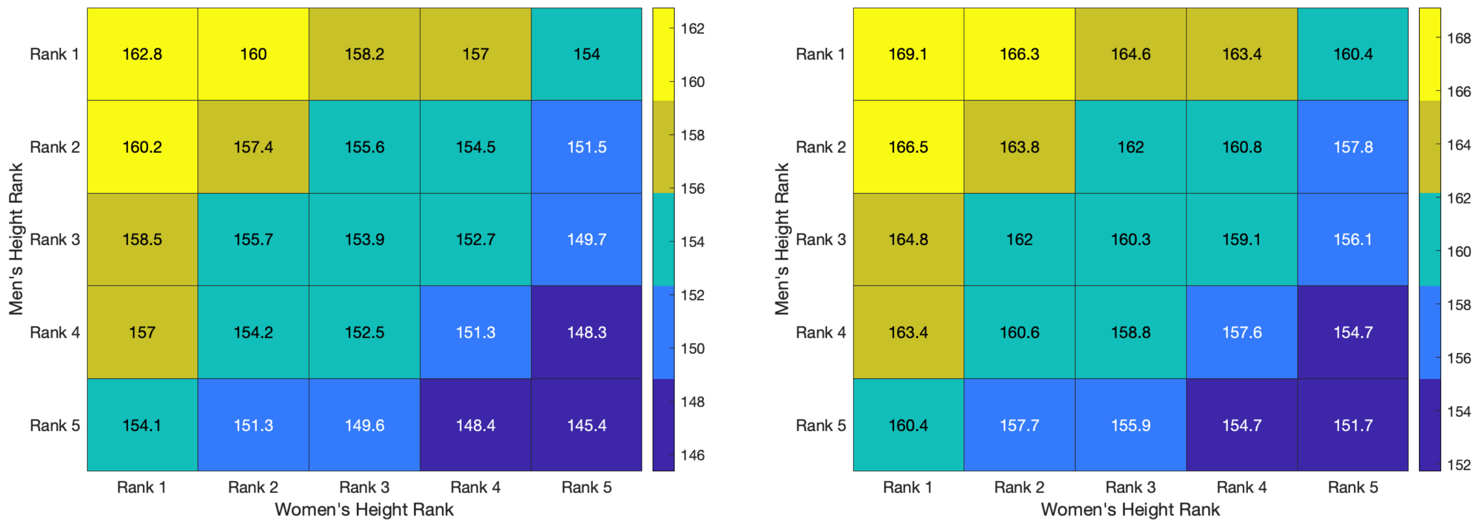


(A) Girl's Potential Distribution

(B) Boy's Potential Distribution

Note: Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970). Counterfactual potential height distribution is calculated under the hypothetical, no complementarity in height in the marriage market.

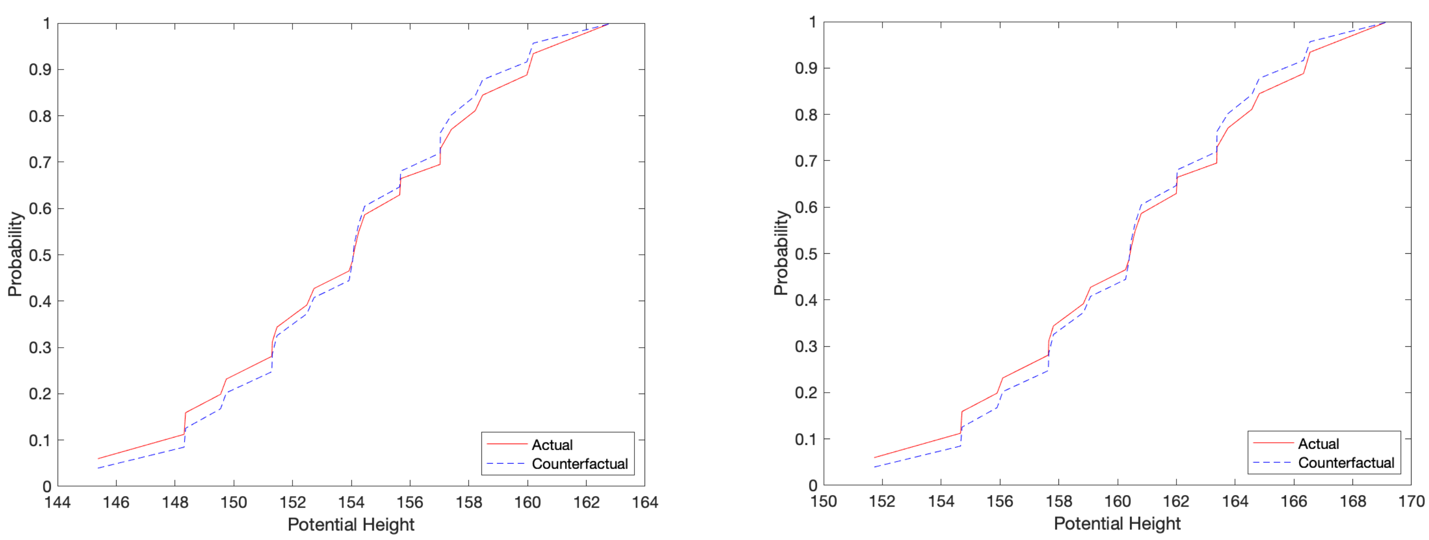
Figure A17: Children's Potential Height: Scheduled Caste



(A) Girl's Potential Height (B) Boy's Potential Height

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970).

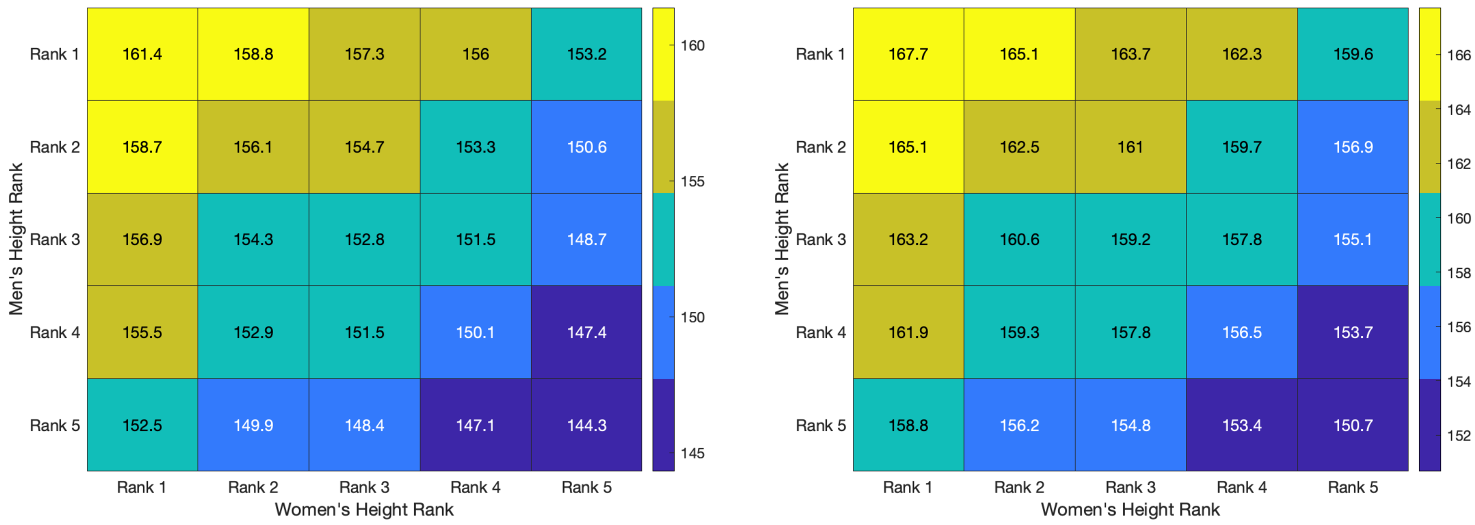
Figure A18: Children's Potential Height Distribution (Scheduled Caste): Actual vs Counterfactual



(A) Girl's Potential Distribution (B) Boy's Potential Distribution

Note: Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970). Counterfactual potential height distribution is calculated under the hypothetical, no complementarity in height in the marriage market.

Figure A19: Children's Potential Height: Scheduled Tribe

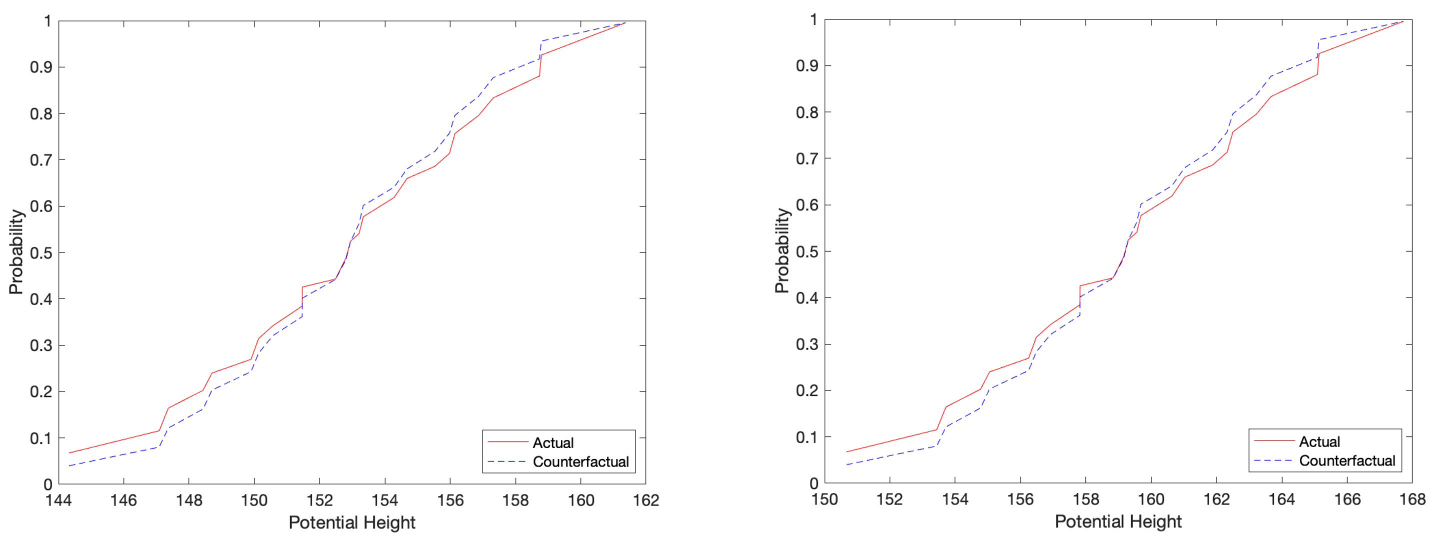


(A) Girl's Potential Height

(B) Boy's Potential Height

Note: Men's height and women's height is divided into 5 ranks. Rank 1 is top 20th percentile, Rank 2 is 20th to 40th percentile, Rank 3 is 40th to 60th percentile, Rank 4 is 60th to 80th percentile and Rank 5 is bottom 20th percentile. Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970).

Figure A20: Children's Potential Height Distribution (Scheduled Tribe): Actual vs Counterfactual

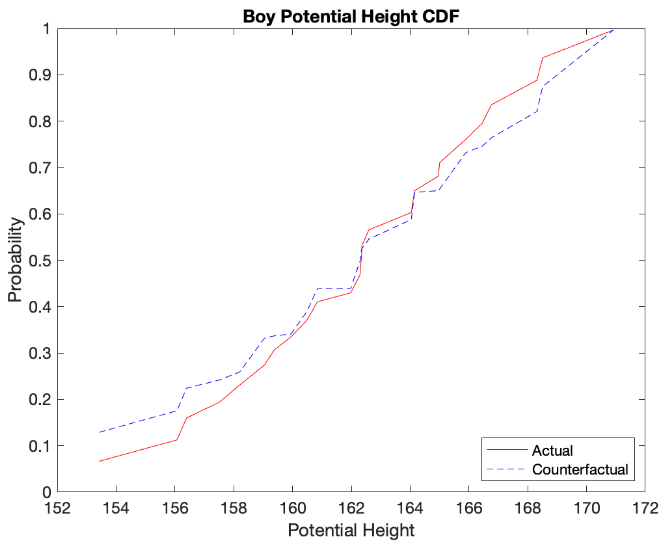


(A) Girl's Potential Distribution

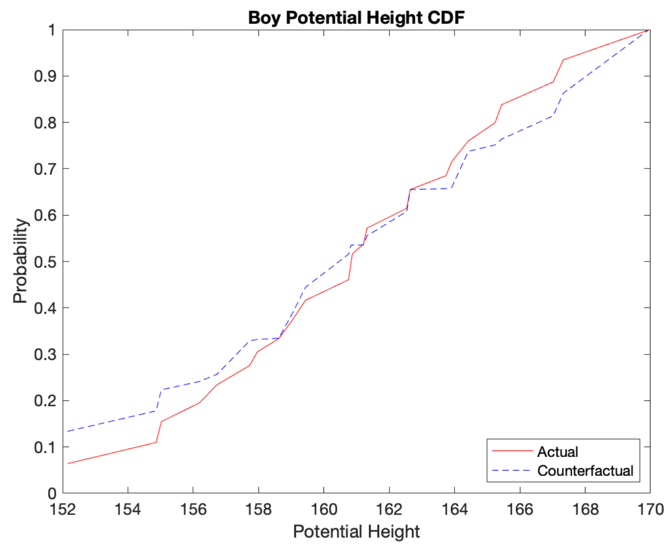
(B) Boy's Potential Distribution

Note: Figure (A) shows the girl's potential height with respect to parental height rank and Figure (B) shows the boy's potential height with respect to parental height rank. Potential height is calculated using Tanner's method (Tanner et al., 1970). Counterfactual potential height distribution is calculated under the hypothetical, no complementarity in height in the marriage market.

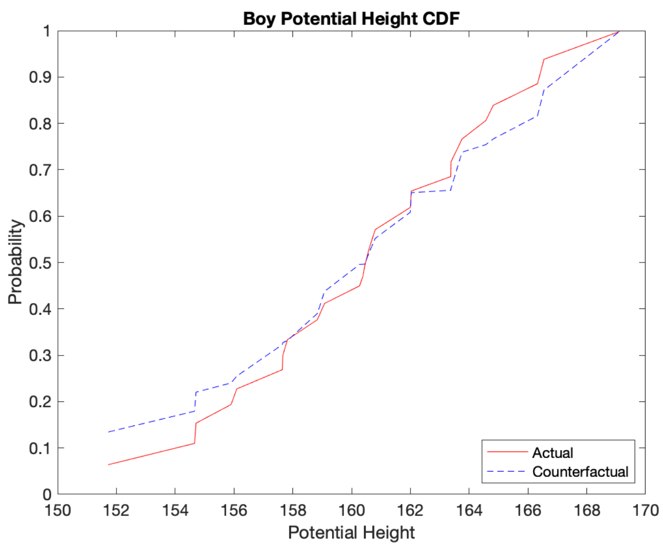
Figure A21: Boy's Potential Height: Actual vs Counterfactual



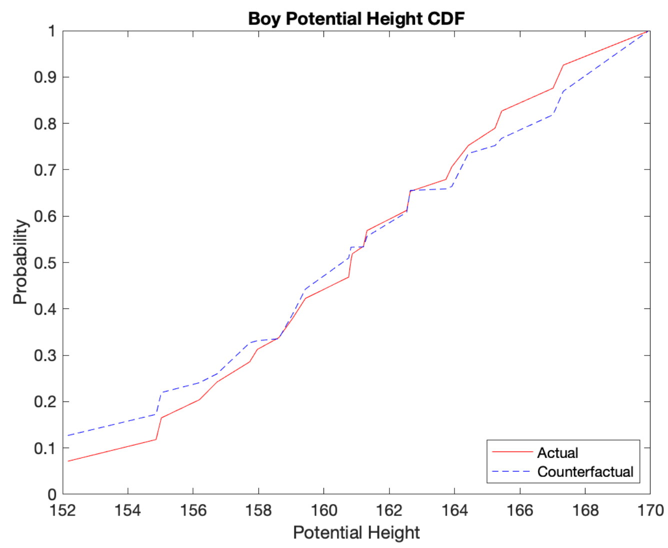
(A) Upper Caste



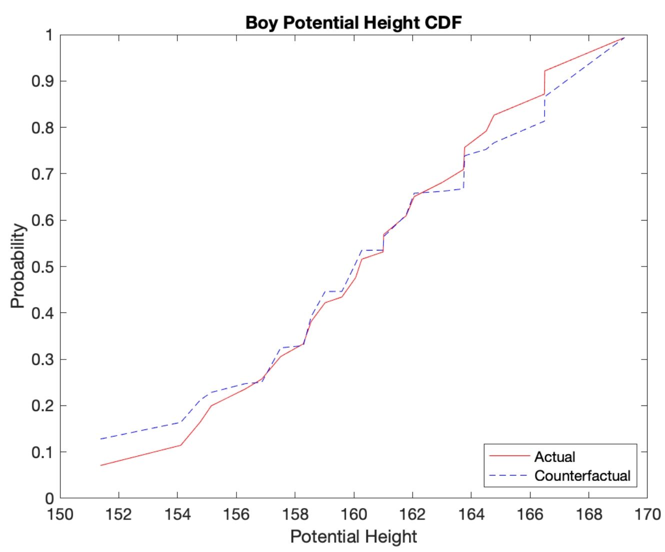
(B) Other Backward Caste



(B) Scheduled Caste



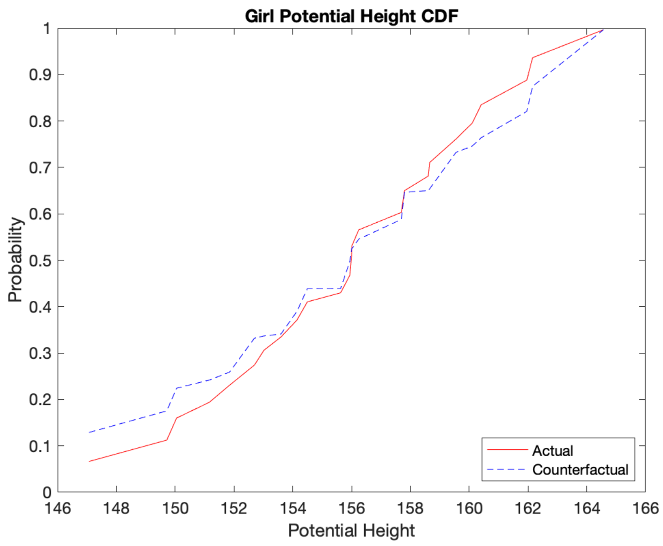
(B) Scheduled Tribe



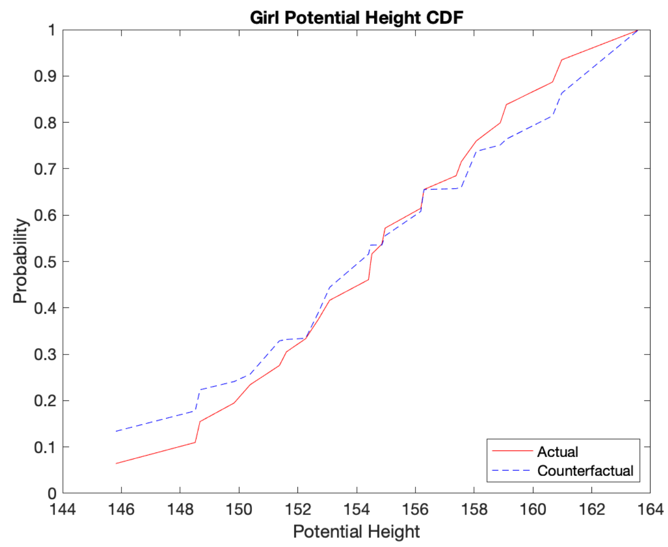
(B) Muslims

Note: The x-axis is the boy's potential height calculated using Tanner's method (Tanner et al., 1970). Counterfactual preferences refer to the hypothetical scenario in which the complementarity in height in the marriage market is the same as the complementarity in age.

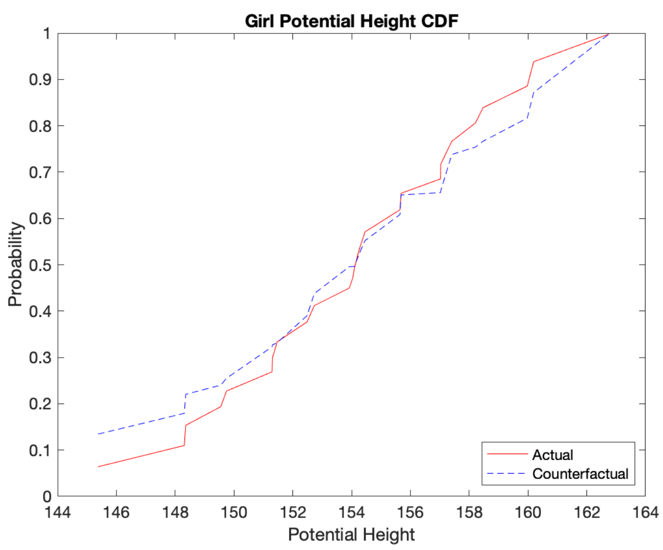
Figure A22: Girl's Potential Height: Actual vs Counterfactual



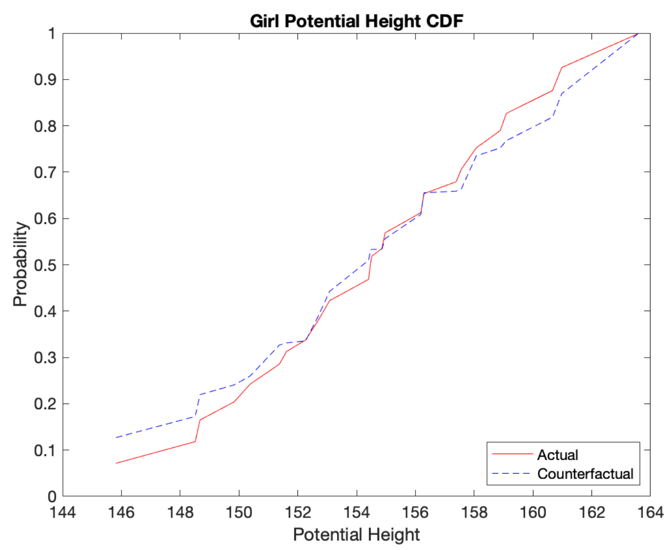
(A) Upper Caste



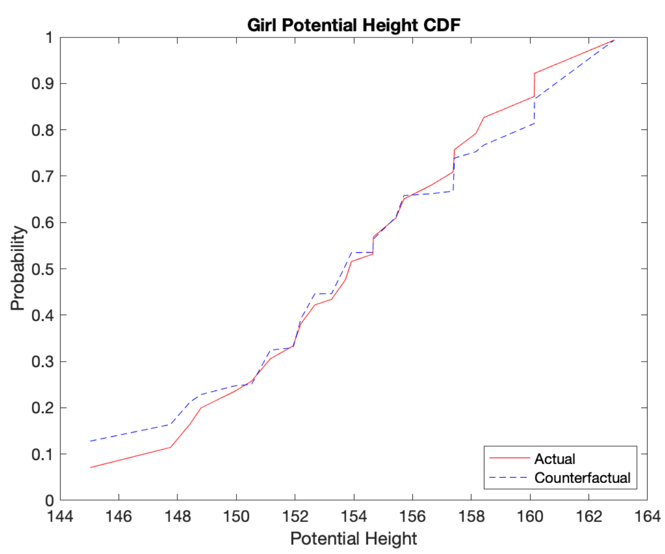
(B) Other Backward Caste



(B) Scheduled Caste



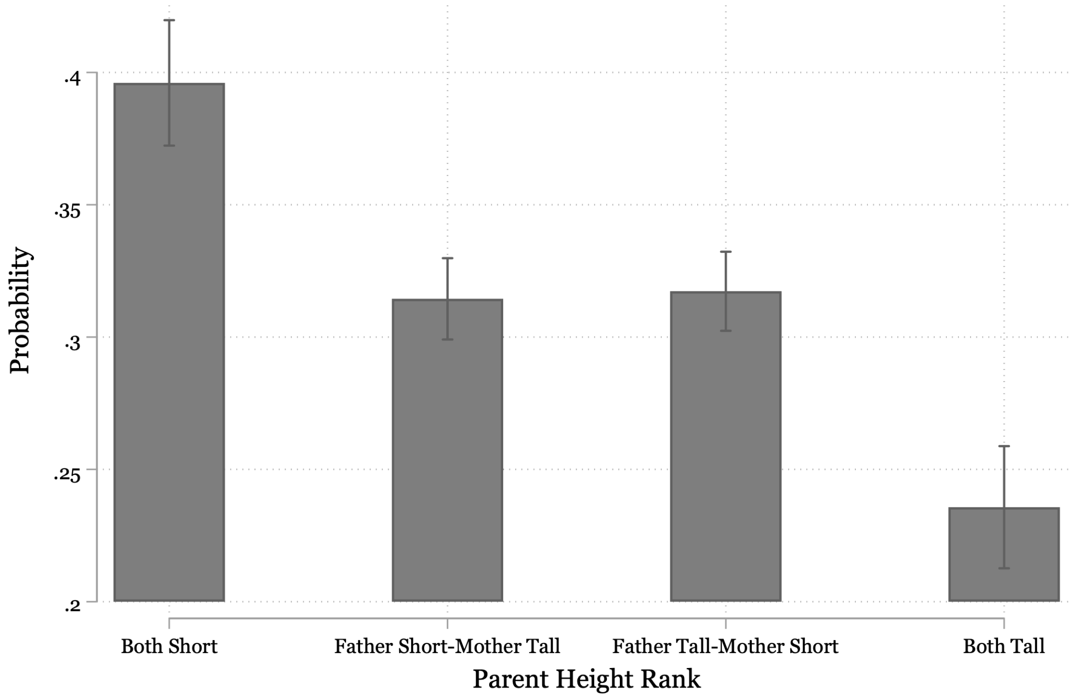
(B) Scheduled Tribe



(B) Muslims

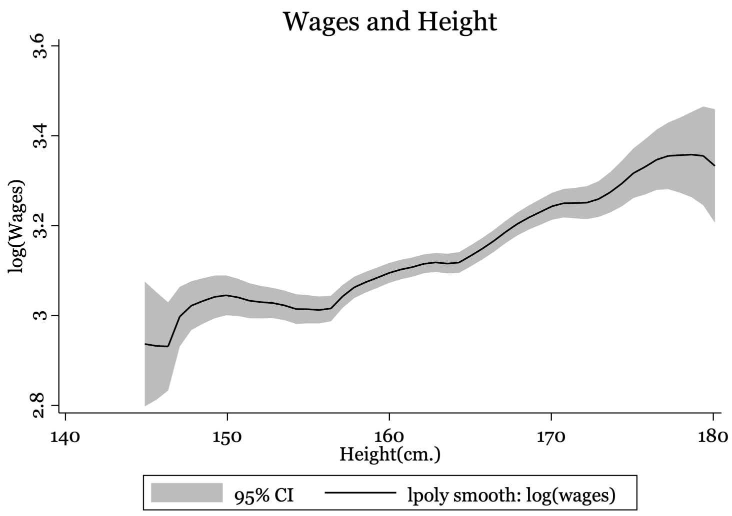
Note: The x-axis is the girl's potential height calculated using Tanner's method (Tanner et al., 1970). Counterfactual preferences refer to the hypothetical scenario in which the complementarity in height in the marriage market is the same as the complementarity in age.

Figure A23: Child Stunting

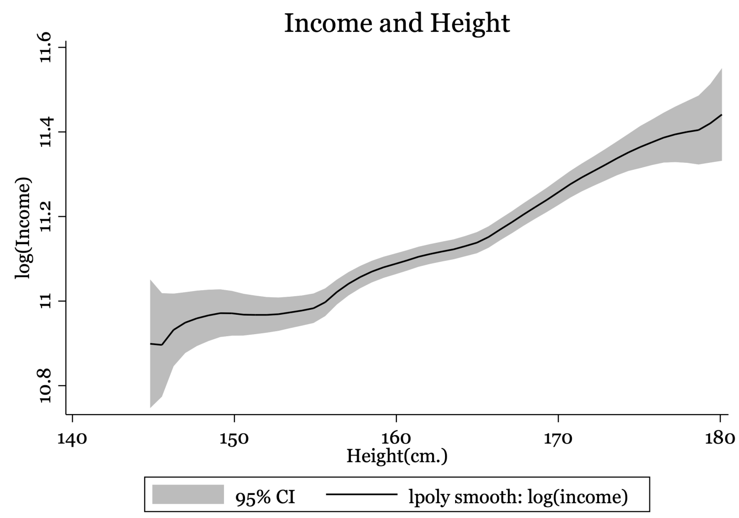


Note: Figure plots the prevalence of child stunting based on mother's and father's height rank conditional on observables consist of the father's education, father's age, paternal grandfather's literacy, paternal grandmother's literacy, mother's education, mother's age, wife's maternal grandfather's literacy and maternal grandmother's literacy, religion-caste group fixed effects, district fixed effects and age fixed effects.

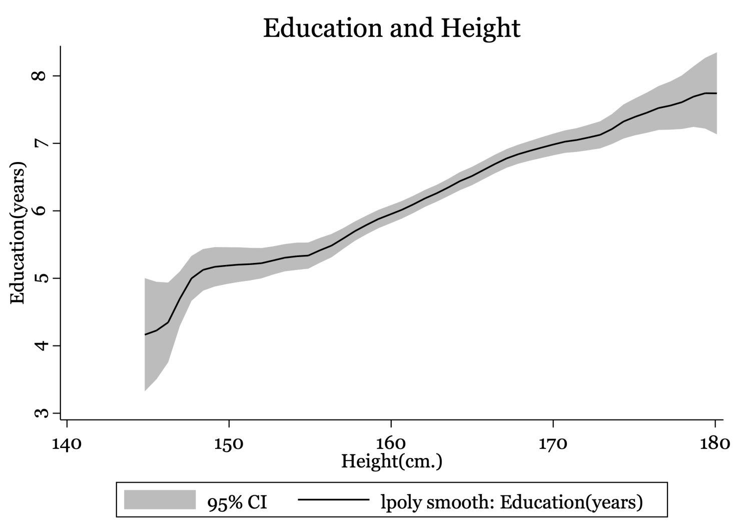
Figure A24: Men's Height, Education, Wages and Income



(A) Men's Wages



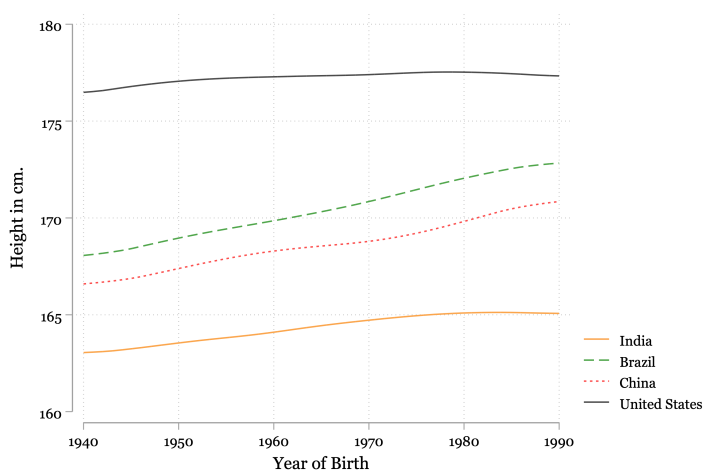
(B) Men's Income



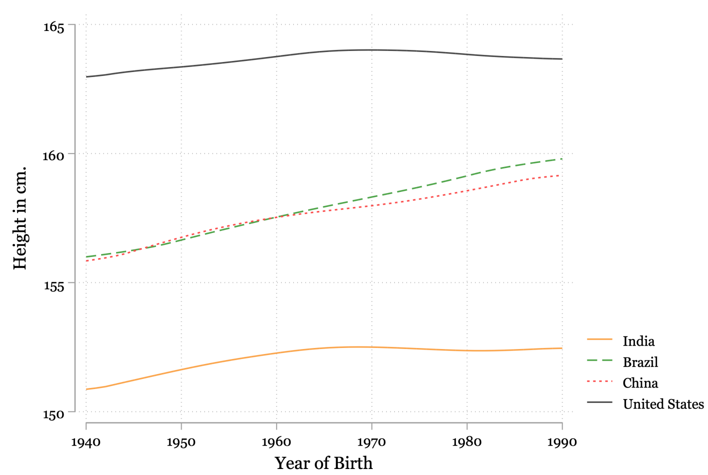
(C) Men's Education

Note: The sample consists of men who are household heads and in the age group 18 to 65.

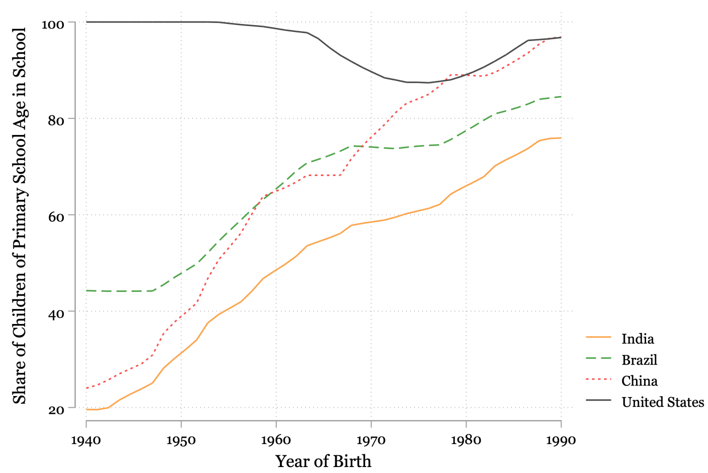
Figure A25: Men and Women's Height and Education over Time



(A) Men's Height



(B) Women's Height



(C) Education

Note: Data Source: Our World in Data: Height Data (Max Roser and Ritchie, 2013) and Education Data (Roser and Ortiz-Ospina, 2013)

Table A1: Conditional Correlation: Sorting on Education

	(1) Husband Education	(2) Wife Education
Wife Education	0.505***	
	(0.023)	
Wife Height	0.016	0.018**
	(0.010)	(0.008)
Husband Height	0.019**	0.011
	(0.007)	(0.007)
Husband Father Education	0.174***	0.074***
	(0.021)	(0.018)
Wife Father Education	0.063***	0.203***
	(0.016)	(0.014)
Husband Mother Education	0.017	0.032
	(0.023)	(0.027)
Wife Mother Education	0.013	0.163***
	(0.031)	(0.020)
Husband Education		0.363***
		(0.017)
Region Fixed Effects	Yes	Yes
Year of Marriage Fixed Effects	Yes	Yes
Covariates	Yes	Yes
Observations	4,652	4,652
Mean of Dep. Variable	7.066	5.218

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: Covariates include religion, caste, age of the husband and age of the wife. Husband and wife's height is measured in centimeters. Education is measured in number of years. Standard errors are clustered at the state level.

Table A2: Conditional Correlation: Sorting on Father Education

	(1) Husband Father Education	(2) Wife Father Education
Wife Father Education	0.168***	
	(0.026)	
Wife Education	0.080***	0.237***
	(0.020)	(0.023)
Husband Education	0.135***	0.053***
	(0.020)	(0.013)
Wife Height	0.008	0.001
	(0.009)	(0.007)
Husband Height	0.021***	0.019*
	(0.007)	(0.010)
Husband Mother Education	0.584***	-0.025
	(0.031)	(0.029)
Wife Mother Education	0.020	0.551***
	(0.023)	(0.031)
Husband Father Education		0.181***
		(0.029)
Region Fixed Effects	Yes	Yes
Year of Marriage Fixed Effects	Yes	Yes
Covariates	Yes	Yes
Observations	4,652	4,652
Mean of Dep. Variable	2.777	3.332

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: Covariates include religion, caste, age of the husband and age of the wife. Husband and wife's height is measured in centimeters. Education is measured in number of years. Standard errors are clustered at the state level.

Table A3: Conditional Correlation: Sorting on Mother Education

	(1) Husband Mother Education	(2) Wife Mother Education
Wife Mother Education	0.233***	
	(0.023)	
Wife Education	0.013	0.085***
	(0.011)	(0.011)
Husband Education	0.005	0.005
	(0.007)	(0.012)
Wife Height	0.000	-0.004
	(0.007)	(0.004)
Husband Height	-0.007	0.005
	(0.005)	(0.005)
Husband Father Education	0.215***	0.009
	(0.022)	(0.011)
Wife Father Education	-0.009	0.246***
	(0.010)	(0.024)
Husband Mother Education		0.307***
		(0.023)
Region Fixed Effects	Yes	Yes
Year of Marriage Fixed Effects	Yes	Yes
Covariates	Yes	Yes
Observations	4,652	4,652
Mean of Dep. Variable	0.941	1.344

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: Covariates include religion, caste, age of the husband and age of the wife. Husband and wife's height is measured in centimeters. Standard errors are clustered at the state level.

Table A4: Summary Statistics: IHDS Sample

	Observations	Mean	St.Dev.	Median	Minimum	Maximum
Husband Height	7355	163.075	6.551	163.000	144.800	180.100
Husband Education	7355	6.165	4.774	7.000	0.000	16.000
Husband Father Education	7355	2.287	3.739	0.000	0.000	16.000
Husband Mother Education	7355	0.707	2.076	0.000	0.000	16.000
Husband Age	7355	44.144	9.708	40.000	30.000	60.000
Wife Height	7355	151.908	6.116	151.300	136.000	168.200
Wife Education	7355	4.096	4.525	3.000	0.000	16.000
Wife Father Education	7355	2.712	4.053	0.000	0.000	16.000
Wife Mother Education	7355	1.024	2.524	0.000	0.000	16.000
Wife Age	7355	39.010	9.145	37.000	20.000	60.000
Height Gap	7355	11.167	7.552	10.400	-20.000	40.500
Education Gap	7355	2.069	4.019	1.000	-12.000	16.000
Age Gap	7355	5.134	2.742	5.000	0.000	13.000
Father Education Gap	7355	-0.425	3.984	0.000	-16.000	16.000
Mother Education Gap	7355	-0.317	2.348	0.000	-16.000	15.000
Natal Family Wealthier	7347	0.171	0.377	0.000	0.000	1.000
Upper Caste	7355	0.186	0.389	0.000	0.000	1.000
Other Backward Caste	7355	0.376	0.484	0.000	0.000	1.000
Scheduled Caste	7355	0.224	0.417	0.000	0.000	1.000
Scheduled Tribe	7355	0.101	0.301	0.000	0.000	1.000
Muslims	7355	0.113	0.316	0.000	0.000	1.000
Observations	7355					

NOTES: Age gap is the difference between the husband's age and the wife's age. Education gap is the difference between husband's education and wife's education. Height gap is the difference between husband's height and wife's height. Father education gap is the difference between husband's father's education and wife's father's education and Mother education gap is the difference between husband's mother's education and wife's mother's education.

Table A5: Child Stunting

	(1) Height Z-Score	(2) Child Stunted
Above Median Rank Father	0.274***	-0.079***
	(0.037)	(0.013)
Above Median Rank Mother	0.388***	-0.082***
	(0.034)	(0.015)
Piped Water	0.100	-0.043*
	(0.060)	(0.022)
Household Expenditure	0.195***	-0.038***
	(0.057)	(0.012)
Female Child	-0.101***	0.020**
	(0.034)	(0.009)
Education Husband	0.002	-0.001
	(0.008)	(0.002)
Education Wife	0.016**	-0.003
	(0.007)	(0.002)
District Fixed Effects	Yes	Yes
Age Fixed Effects	Yes	Yes
Caste-Religion Fixed Effects	Yes	Yes
Observations	8,119	8,119
Mean of Dep. Variable	-1.292	0.315

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: A child is defined as stunted if their height-for-age z-score is 2 SD or more below the reference population median for a given age and gender. Observables consist of the father's education, father's age, paternal grandfather's literacy, paternal grandmother's literacy, mother's education, mother's age, wife's maternal grandfather's literacy and maternal grandmother's literacy. Religion-Caste specific groups consist of Scheduled Caste, Scheduled Tribe, Other Backward Caste, Upper Caste and Muslims. Standard errors are clustered at the state-level.

Table A6: Men's Height Premium in India

	(1) log(wages)	(2) log(income)	(3) Regular Full-time Job
Height(cm.)	0.0077***	0.0100***	0.0022**
	(0.0013)	(0.0017)	(0.0008)
Education(years)	0.0250***	0.0315***	0.0220***
	(0.0026)	(0.0022)	(0.0013)
State Fixed Effects	Yes	Yes	Yes
Caste-Religion Fixed Effects	Yes	Yes	Yes
Covariates	Yes	Yes	Yes
Observations	9,026	13,329	9,221
Mean of Dep. Variable	3.117	11.119	0.197

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

NOTES: Sample consists of men who are household heads and in the age group 18 to 65. Wages represent in Covariates consist of individual's english ability, father's education, mother's education, number of brothers and sisters, age and age squared. Caste-Religion groups consist of Upper Caste, Other Backward Caste, Scheduled Caste, Scheduled Tribe and Muslims. Regular Full-time job is 1 if the individual has a Regular/Permanent/Longer contract job and 0 if the individual has a casual daily, casual piecework or a less than 1 year contract job. Standard errors are clustered at the state-level.

Table A7: Affinity Matrix Estimates: Upper Caste (Old Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.31***	-0.009	0.072*	0.025	0.236***
	(0.04)	(0.052)	(0.048)	(0.039)	(0.054)
Education	0.044	0.937***	0.229***	0.011	0.039
	(0.052)	(0.078)	(0.063)	(0.054)	(0.073)
Father Education	-0.047	0.177***	0.286***	0.035	0.105*
	(0.047)	(0.065)	(0.053)	(0.044)	(0.066)
Mother Education	0.014	0.104*	0.038	0.168***	-0.097
	(0.043)	(0.064)	(0.047)	(0.033)	(0.061)
Age	-0.014	-0.002	-0.113	0.062*	1.28***
	(0.049)	(0.067)	(0.06)	(0.048)	(0.083)

Note: Each element represents the complementarity/ substitutability between two features. Data consists of individuals belonging to the Upper Caste, with men between the age of 50 and 60 and women between the age of 40 and 60.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A8: Affinity Matrix Estimates: Other Backward Caste (Old Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.264***	0.053*	0.005	0.096**	0.103***
	(0.03)	(0.037)	(0.047)	(0.052)	(0.041)
Education	-0.004	0.882***	0.289***	-0.086	0.069
	(0.045)	(0.061)	(0.061)	(0.068)	(0.061)
Father Education	-0.041	0.046	0.416***	-0.009	-0.004
	(0.047)	(0.059)	(0.057)	(0.064)	(0.065)
Mother Education	-0.039	0.341***	-0.106	0.258***	-0.01
	(0.052)	(0.067)	(0.055)	(0.05)	(0.07)
Age	0.048	0.23***	-0.145	0.095*	1.337***
	(0.039)	(0.049)	(0.059)	(0.063)	(0.066)

Note: Each element represents the complementarity/ substitutability between two features. The old cohort consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A9: Affinity Matrix Estimates: Scheduled Tribe (Old Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.232***	0.081	-0.069	0.05	0.198**
	(0.07)	(0.1)	(0.153)	(0.167)	(0.104)
Education	-0.034	1.052***	0.575***	-0.003	0.13
	(0.13)	(0.166)	(0.215)	(0.244)	(0.183)
Father Education	-0.062	0.354**	0.568***	-0.218	-0.254
	(0.165)	(0.2)	(0.236)	(0.255)	(0.236)
Mother Education	0.065	0.048	-0.071	0.714***	0.265
	(0.174)	(0.252)	(0.257)	(0.242)	(0.225)
Age	-0.044	0.295***	0.058	-0.183	1.555***
	(0.089)	(0.116)	(0.204)	(0.206)	(0.157)

Note: Each element represents the complementarity/ substitutability between two features. The old cohort consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A10: Affinity Matrix Estimates: Scheduled Caste (Old Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.319*** (0.047)	-0.079 (0.057)	0.099 (0.091)	0.141* (0.1)	0.271*** (0.061)
Education	0.068 (0.082)	1.017*** (0.102)	0.13 (0.122)	0.241** (0.123)	-0.008 (0.104)
Father Education	-0.072 (0.091)	0.362*** (0.108)	0.472*** (0.12)	-0.149 (0.124)	0.199** (0.116)
Mother Education	0.101 (0.122)	0.044 (0.156)	-0.126 (0.142)	0.315*** (0.104)	-0.113 (0.155)
Age	-0.02 (0.059)	0.073 (0.072)	0.063 (0.116)	0.009 (0.121)	1.331*** (0.095)

Note: Each element represents the complementarity/ substitutability between two features. The old cohort consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A11: Affinity Matrix Estimates: Muslims (Old Cohort)

	Woman				
Man	Height	Education	Father Education	Mother Education	Age
Height	0.272*** (0.058)	0.047 (0.075)	0.061 (0.092)	0.006 (0.089)	0.097* (0.074)
Education	0.144* (0.097)	0.885*** (0.126)	0.143 (0.131)	0.074 (0.119)	-0.062 (0.128)
Father Education	0.083 (0.103)	0.16 (0.131)	0.441*** (0.118)	-0.169 (0.128)	0.276** (0.133)
Mother Education	-0.132 (0.125)	0.178 (0.157)	-0.11 (0.153)	0.369*** (0.121)	-0.163 (0.169)
Age	0.009 (0.076)	0.003 (0.103)	0.1 (0.129)	-0.173 (0.122)	1.329*** (0.128)

Note: Each element represents the complementarity/ substitutability between two features. The old cohort consists of men born between 1950 and 1960 and their spouses born between 1950 and 1970.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A12: Affinity Matrix (REDS 2006 Sample) : Other Backward Caste (Young Cohort)

	Woman			
Man	Height	Education	Wealth	Age
Height	0.531*** (0.078)	-0.182 (0.061)	-0.002 (0.084)	0.407*** (0.096)
Education	0.007 (0.076)	0.678*** (0.084)	0.295*** (0.103)	0.159* (0.118)
Wealth	-0.02 (0.088)	-0.109 (0.102)	0.298*** (0.082)	0.09 (0.181)
Age	-0.029 (0.115)	0.32*** (0.113)	0.182* (0.141)	2.854*** (0.232)

Note: Affinity matrix estimated using the REDS 2006 sample. Each element represents the complementarity/substitutability between two features. Data consists of individuals belonging to the Other Backward Caste, with men between the age of 30 and 40 and women between the age of 20 and 40.
Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A13: Affinity Matrix (REDS 2006 Sample) : Upper Caste (Young Cohort)

	Woman			
Man	Height	Education	Wealth	Age
Height	0.612***	-0.314	0.228***	0.416***
	(0.121)	(0.117)	(0.097)	(0.167)
Education	-0.068	1.064***	0.218***	-0.137
	(0.103)	(0.15)	(0.088)	(0.158)
Wealth	0.083	0.04	0.39***	0.256**
	(0.084)	(0.117)	(0.073)	(0.142)
Age	-0.159	0.037	-0.156	2.33***
	(0.146)	(0.163)	(0.135)	(0.285)

Note: Affinity matrix estimated using the REDS 2006 sample. Each element represents the complementarity/substitutability between two features. Data consists of individuals belonging to the Upper Caste, with men between the age of 30 and 40 and women between the age of 20 and 40. Standard errors are in the parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table A14: Joint Utility Share Explained: Other Backward Caste

	Index 1	Index 2	Index 3	Index 4	Index 5
Share of joint utility explained	67.63	16.63	7.91	4.89	2.94
Standard deviation of shares	0.81	1.27	0.88	0.76	3.71

NOTES: The table shows the five indices, Index 1 - Index 5, explaining mutually exclusively shares of the joint marital utility using the Saliency analysis technique in Dupuy and Galichon (2014). Standard errors are calculated using 500 bootstrap replications. Coefficient in red shows the share of joint marital utility explained by height of the man and the woman.

Table A15: Loading Matrix: Other Backward Caste

	Index 1		Index 2		Index 3		Index 4		Index 5	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Height	-0.09	-0.07	0.09	0.17	0.92	0.83	-0.36	-0.51	0.00	-0.15
Education	-0.08	-0.16	0.94	0.94	-0.04	-0.24	0.14	-0.01	-0.31	-0.19
Father Education	-0.03	0.05	0.14	0.24	0.24	0.47	0.66	0.70	0.70	0.47
Mother Education	0.00	-0.03	0.30	0.11	-0.28	-0.17	-0.65	-0.49	0.64	0.85
Age	-0.99	-0.98	-0.08	-0.16	-0.08	0.01	0.00	0.09	0.01	0.04

NOTES: The table shows indices of mutual attractiveness (Dupuy and Galichon, 2014) for men and women as a weighted sum of marriage market features. The total share of joint utility explained by an index is given in table A14. Coefficient in red corresponds to the index of mutual attractiveness for men and women with the largest weight corresponding to height.

Table A16: Joint Utility Share Explained: Scheduled Caste

	Index 1	Index 2	Index 3	Index 4	Index 5
Share of joint utility explained	65.22	18.86	8.27	5.22	2.43
Standard deviation of shares	1.09	1.67	1.07	0.84	4.36

NOTES: The table shows the five indices, Index 1 - Index 5, explain mutually exclusively shares of the joint marital utility using the Saliency analysis technique in Dupuy and Galichon (2014). Standard errors are calculated using 500 bootstrap replications. Coefficient in red shows the share of joint marital utility explained by height of the man and the woman.

Table A17: Factor Loadings: Scheduled Caste

	Index 1		Index 2		Index 3		Index 4		Index 5	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Height	-0.09	-0.03	0.13	0.07	0.97	0.88	-0.18	-0.47	-0.03	0.02
Education	-0.08	-0.12	0.94	0.95	-0.16	-0.12	-0.14	-0.09	-0.25	-0.24
Father Education	0.00	0.05	0.29	0.27	0.11	0.28	0.72	0.59	0.62	0.71
Mother Education	0.01	-0.04	0.08	0.05	-0.11	-0.37	-0.65	-0.65	0.75	0.66
Age	-0.99	-0.99	-0.09	-0.10	-0.08	0.02	0.02	0.08	0.03	0.04

NOTES:The table shows indices of mutual attractiveness (Dupuy and Galichon, 2014) for men and women as a weighted sum of marriage market features. The total share of joint utility explained by an index is given in table A16. Coefficient in red corresponds to the index of mutual attractiveness for men and women with the largest weight corresponding to height.

Table A18: Joint Utility Share Explained: Scheduled Tribe

	Index 1	Index 2	Index 3	Index 4	Index 5
Share of joint utility explained	61.07	21.66	10.96	4.29	2.02
Standard deviation of shares	1.81	2.67	1.72	1.31	6.10

NOTES: The table shows the five indices, Index 1 - Index 5, explain mutually exclusively shares of the joint marital utility using the Saliency analysis technique in Dupuy and Galichon (2014). Standard errors are calculated using 500 bootstrap replications. Coefficient in red shows the share of joint marital utility explained by height of the man and the woman.

Table A19: Factor Loadings: Scheduled Tribe

	Index 1		Index 2		Index 3		Index 4		Index 5	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Height	-0.02	-0.03	-0.08	-0.00	0.98	0.99	-0.15	-0.08	0.00	0.09
Education	0.00	0.04	0.99	0.96	0.08	0.03	0.00	-0.06	0.09	-0.26
Father Education	0.09	-0.05	-0.02	0.13	0.15	0.05	0.98	0.95	0.03	0.28
Mother Education	-0.09	0.08	0.09	-0.24	0.02	0.11	0.04	0.30	-0.99	-0.91
Age	0.99	0.99	0.01	-0.02	0.01	0.02	-0.09	0.02	-0.10	0.10

NOTES: The table shows indices of mutual attractiveness (Dupuy and Galichon, 2014) for men and women as a weighted sum of marriage market features. The total share of joint utility explained by an index is given in table A18. Coefficient in red corresponds to the index of mutual attractiveness for men and women with the largest weight corresponding to height.

Table A20: Joint Utility Share Explained: Muslims

	Index 1	Index 2	Index 3	Index 4	Index 5
Share of joint utility explained	58.34	19.56	11.11	8.49	2.50
Standard deviation of shares	1.60	2.40	1.67	1.38	5.50

NOTES: The table shows the five indices, Index 1 - Index 5, explain mutually exclusively shares of the joint marital utility using the Saliency analysis technique in Dupuy and Galichon (2014). Standard errors are calculated using 500 bootstrap replications. Coefficient in red shows the share of joint marital utility explained by height of the man and the woman.

Table A21: Factor Loadings: Muslims

	Index 1		Index 2		Index 3		Index 4		Index 5	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Height	0.16	0.03	0.03	-0.09	0.91	0.92	0.35	0.35	0.13	-0.13
Education	0.06	0.15	-0.94	-0.96	0.09	-0.05	-0.06	-0.16	-0.32	-0.15
Father Education	-0.09	-0.17	-0.28	-0.22	-0.32	-0.27	0.67	0.82	0.60	0.42
Mother Education	0.06	0.07	-0.19	-0.08	0.14	0.26	-0.64	-0.38	0.73	0.88
Age	0.98	0.97	0.04	0.12	-0.19	-0.08	0.05	0.18	0.01	0.04

NOTES:The table shows indices of mutual attractiveness (Dupuy and Galichon, 2014) for men and women as a weighted sum of marriage market features. The total share of joint utility explained by an index is given in table A20. Coefficient in red corresponds to the index of mutual attractiveness for men and women with the largest weight corresponding to height.

Table A22: Joint Utility Share Explained: Upper Caste

	Index 1	Index 2	Index 3	Index 4	Index 5
Share of joint utility explained	52.95	24.78	12.13	6.89	3.26
Standard deviation of shares	1.27	2.82	1.87	1.59	4.65

NOTES: The table shows the five indices, Index 1 - Index 5, explain mutually exclusively shares of the joint marital utility using the Saliency analysis technique in Dupuy and Galichon (2014). Standard errors are calculated using 500 bootstrap replications.

Table A23: Factor Loadings: Upper Caste

	Index 1		Index 2		Index 3		Index 4		Index 5	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Height	0.02	-0.02	-0.02	0.03	-0.53	-0.49	0.72	0.81	-0.44	-0.31
Education	0.11	0.18	0.90	0.96	-0.08	0.11	0.19	0.09	0.37	0.16
Father Education	0.01	-0.07	0.10	0.18	-0.77	-0.80	-0.62	-0.55	-0.08	-0.16
Mother Education	0.08	0.09	0.41	0.11	0.34	0.32	-0.24	-0.17	-0.81	-0.92
Age	0.99	0.98	-0.13	-0.17	0.00	-0.12	-0.01	-0.03	0.03	0.04

NOTES: The table shows indices of mutual attractiveness (Dupuy and Galichon, 2014) for men and women as a weighted sum of marriage market features. The total share of joint utility explained by an index is given in table A22.