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Pierre-André Chiappori
Sonia Oreffice
Climent Quintana-Domeque

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Department of Economics
Columbia University
New York, NY 10027

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Fatter attraction: anthropometric and socioeconomic matching on the marriage market*

Pierre-André Chiappori
Columbia University

Sonia Oreffice
Universitat d'Alacant and IZA

Climent Quintana-Domeque
Universitat d'Alacant

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Abstract

We construct a matching model on the marriage market along more than one characteristic, where individuals have preferences over physical attractiveness and socioeconomic characteristics that can be summarized by a one-dimensional index combining these various attributes. We show that under a (testable) separability assumption, the indices are ordinally identified. We estimate the model using data from the PSID. Our separability tests do not reject. We find that among men, a 10% increase in BMI can be compensated by a higher wage of around 3%. Similarly, for women, an additional year of education may compensate up to three BMI units.

Keywords: BMI, marriage market, wages, education.
JEL Codes: D1, J1.

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1 Introduction

The analysis of matching patterns in the population has recently attracted considerable attention, from both a theoretical and an empirical perspective. Most models focus on exactly one characteristic on which the matching process is assumed to be exclusively based. Various studies have thus investigated the features of assortative matching on income, wages or education (e.g., Becker, 1991; Pencavel, 1998; Wong, 2003; Chow and Siow, 2006; Flinn and Del Boca, 2007), but also on such preference-based notions as risk aversion (e.g., Chiappori and Reny, 2004; Legros and Newman, 2007) or desire to have a child (Chiappori and Oreffice, 2008).

One-dimensional matching models offer several advantages. Their formal properties are by now well established. In a transferable utility context, they provide a simple and elegant way to explain the type of assortative matching patterns that are currently observed; namely, the stable match is positive (negative) assortative if and only if the surplus function is super (sub) modular. Moreover, it is possible, from the shape of the surplus function, to recover the equilibrium allocation of resources within each match, a feature that proves especially useful in many theoretical approaches. Arguments of this type have been applied, for instance, to explain why female demand for university education may outpace that of men (Chiappori, Iyigun and Weiss, 2009), or how women unwilling to resort to abortion still benefited from its legalization (Chiappori and Oreffice, 2008).

These advantages, however, come at a cost. The transferable utility assumption generates strong restrictions. For instance, the efficient decision at the group level does not depend on the distribution of Pareto weights within the group. This implies not only that the group behaves as a single individual - a somewhat counterfactual statement, as illustrated by numerous empirical studies - but also that a redistribution of powers, say to the wife, cannot by assumption alter the group's aggregate behavior. Secondly, matching models with supermodular surplus can only predict *perfectly* assortative matching - while reality is obviously much more complex, if only because of the role played by chance (or unobservable factors) in the assignments. Thirdly, and more importantly, empirical evidence strongly suggests that, in real life, matching processes are actually multidimensional; spouses tend to be similar in a variety of characteristics, including age, education, race, religion, and anthropometric characteristics such as weight or height (e.g., Becker, 1991; Weiss and Willis, 1997; Qian, 1998; Silventoinen et al., 2003; Hitsch, Hortaçsu and Ariely, 2010; Oreffice and Quintana-Domeque, 2010).

Each of these criticisms has, in turn, generated further research aimed at adressing the corresponding concerns. Models of frictionless matching without transferable utility have been developed by Chiappori and Reny (2004), Legros and Newman (2007) and Browning, Chiappori and Weiss (2010). Following the seminal, theoretical contribution by Shimer and Smith (2000), several empirical contributions (Choo and Siow, 2006; Chiappori, Salanié and Weiss, 2010) introduce randomness into the matching process, to account for the deviations from perfectly assortative matching that characterize actual data. Finally, Hitsch et al. (2010), working on online dating, introduce several dimensions by modelling individual utility as a linear valuation of the mates' attributes within a Gale-Shapley framework (in which transfers between mates are ruled out). However, they lack the relevant information on the matches actually formed. Still within a Gale-Shapley framework, Banerjee, Duflo, Ghatak and Lafortune (2009) consider newspaper weddings ads in India providing information on height, physical appearance, caste and income of potential spouses to analyze the value of caste. Perhaps more interestingly, Galichon and Salanié (2009) explicitly model multidimensional matching in a frictionless framework under transferable utility.

The goal of the present paper is to *simultaneously* address the concerns described above. We investigate the relative importance on the marriage market of anthropometric and socioeconomic characteristics, and the way men and women assess these characteristics; our approach is therefore intrinsically multi-dimensional. In addition, we assume that some of the relevant characteristics are not observable to the econometrician; as a consequence, the matching process is partly random, at least from an exterior perspective, and does not result in a perfectly assortative outcome. Finally, we do not focus on a specific setting or matching game. Our approach is compatible with a large variety of matching mechanisms, including frictionless models with and without transferable utility, random matching à la Shimer and Smith, search models and others. Our empirical strategy relies on a crucial assumption - namely, that individual 'attractiveness' on the marriage market is fully determined by an index that depends on the agent's (observable and non observable) characteristics, and that this index is moreover weak separable in the observable variables. We show that, under this assumption, it is possible to non-parametrically identify the form of the relevant indices up to some increasing transform. In particular, one can non-parametrically recover the trade-off between the various observable dimensions that characterize each individual. Technically, the index we postulate allows to define 'iso-attractiveness profiles' and marginal rates of substitution between the different individual characteristics; we show that these profiles and MRSs are exactly identified from the matching patterns.

Our weak separability assumption, while parsimonious, is certainly restrictive. We show, however, that it is testable, and we provide a set of necessary and sufficient conditions that have to be satisfied for the assumption to hold. In the end, whether the assumption is acceptable becomes therefore an empirical issue. We apply our approach to marital trade-offs in the United States, using data from the Panel Study of Income Dynamics (PSID), which contains anthropometric and socioeconomic characteristics of married men and women from 1999 to 2007. We proxy a man's socio-economic status by his wage; for women, since participation is a serious issue (a significant fraction of females in our sample do not work), we use education as our main socioeconomic variable. Regarding non-economic characteristics, the PSID provides data on individual weight and height, which we use to construct the individual body mass index (BMI), our main proxy for non-economic (physical) attractiveness. Our specification tests, which characterize the implication of the weak separability assumption, do not reject the assumption; this result is surprisingly robust. We can therefore identify the trade-offs between economic and non-economic aspects; we find, for instance, that a 10% increase in BMI can be compensated by a higher wage, the supplement being estimated to be around 3%. Similarly, for women, an additional year of education may compensate up to three BMI units. Interestingly, male physical attractiveness matters as well.

Our work is related to a large economic research agenda on the effects of anthropometric measures. Many economists have been working on assessing the effects of height, weight and BMI on labor-market outcomes. The consensus is that BMI in the overweight or obese range has negative effects on the probability of employment and on hourly wages, particularly for women (Cawley, 2000; Cawley, 2004; Han, Norton, and Stearns, 2009), while height has a positive effect on hourly wages, perhaps reflecting the fact that taller people are more likely to have reached their full cognitive potential (Case and Paxson, 2008) and/or may possess superior physical capacities (Lundborg, Nystedt, Rooth, 2009). A related body of literature using National Longitudinal Survey of Youth data links women's weight to lower spousal earnings or lower likelihood of being in a relationship (Averett and Korenman, 1996; Averett, Sikora and Argys, 2008; Mukhopadhyay, 2008; Tosini, 2009). However, these data provide anthropometric measures of the respondent only, so that the weight-income trade-off across spouses is estimated without controlling for the men's physical attributes. The same can be said about the influential work by Hamermesh and Biddle (1994), which shows that physically unattractive women are matched with less educated husbands. Assortative mating in body weights has been established in the medical and psychological literatures, which document significant and positive interspousal correlations for weight (Schafer and Keith, 1990; Allison et al., 1996; Speakman et al., 2007), and the importance of examining the effect of both spouses' characteristics on their marriage (Fu and Goldman, 2000; Jeffrey and Rick, 2002; McNulty and Neff, 2008).

The paper is organized as follows. Section 2 presents the formal framework on which our approach is based. Section 3 discusses how to measure attractiveness that mates care about. Section 4 describes the data used in the empirical analysis. Section 5 shows the matching patterns we observe in the data. Section 6 provides a formal test of our model and its empirical results. Section 7 considers some extensions. Finally, section 8 concludes.

2 The model

We consider a population of men and a population of women. Each potential husband, say $i \in I$, is characterized by a vector $X_i = \left(X_i^1, ..., X_i^K\right)$ of observable characteristics, and by some vector of unobservable characteristics $\varepsilon_i \in \mathbb{R}^S$ the distribution of which is centered and independent of X. Similarly, woman $j \in J$ is defined by a vector of observable variables $Y_j = \left(Y_j^1, ..., Y_j^L\right)$ and some unobservable characteristics $\eta_j \in \mathbb{R}^S$ which are centered and independent of Y.

Our key assumption is the following:

Assumption I *The 'attractiveness' of male i (resp. female j) on the marriage market is fully summarized by a one-dimensional index $I_i = F\left(X_i^1, ..., X_i^K, \varepsilon_i\right)$ (resp. $J_j = G\left(Y_j^1, ..., Y_j^L, \eta_j\right)$). Moreover, these indices are weakly separable in $\left(X_i^1, ..., X_i^K\right)$ and $\left(Y_j^1, ..., Y_j^L\right)$ respectively; i.e.*

$$\begin{aligned} I_i &= i\left(I\left(X_i^1, ..., X_i^K\right), \varepsilon_i\right) \\ & \quad \textit{and} \\ J_j &= j\left(J\left(Y_j^1, ..., Y_j^L\right), \eta_j\right) \end{aligned} \tag{1}$$

for some mappings i, j from $\mathbb{R}^{S+1}$ to $\mathbb{R}$ and I (resp. J) from $\mathbb{R}^K$ (resp. R^L) to $\mathbb{R}$.

In practice, our assumption has the following implication. Assume that we observe the marital patterns in the population under consideration - i.e., the joint density $d\mu\left(X^1, ..., X^K, Y^1, ..., Y^L\right)$ of observables among married couples. Then this density has the form:

$$d\mu\left(X^1, ..., X^K, Y^1, ..., Y^L\right) = d\nu\left[I\left(X^1, ..., X^K\right), J\left(Y^1, ..., Y^L\right)\right]$$

for some measure $d\nu$ on $\mathbb{R}^2$. In particular, the conditional distribution of $\left(Y^1, ..., Y^L\right)$ given $\left(X^1, ..., X^K\right)$ only depends on the value $I\left(X^1, ..., X^K\right)$; similarly, the conditional distribution of $\left(X^1, ..., X^K\right)$ given $\left(Y^1, ..., Y^L\right)$ only depends on the value $J\left(Y^1, ..., Y^L\right)$. In other words, the subindex I, which only depends on observables, is a sufficient statistic for the distribution of characteristics of a man's spouse; and the same holds with subindex J for women. Note that this property holds irrespective of the specific matching game that is played between agents; we simply assume that, from a male's viewpoint, two women j and j' with different profiles $\left(Y_j^1, ..., Y_j^L\right)$ and $\left(Y_{j'}^1, ..., Y_{j'}^L\right)$ but identical indices $J\left(Y_j^1, ..., Y_j^L\right) = J\left(Y_{j'}^1, ..., Y_{j'}^L\right)$ offer equivalent marital prospects, so that any difference between their mates' respective profiles must be purely driven by the unobservable characteristics - i.e., is seen by the econometrician as random (and similarly for men).

An important consequence is that it is in general possible, from data on the matching patterns, to (ordinally) identify the underlying, attractiveness indices. Indeed, the expected value of the kth characteristic of the wife, conditional on the vector of characteristics of the husband, is of the form:

$$E\left[Y^s \mid X_i^1, ..., X_i^K\right] = \phi_s\left[I\left(X_i^1, ..., X_i^K\right)\right] \tag{2}$$

for some function ϕ_s. This shows that the function I is identified up to some transform (here ϕ_s). It follows that the trade-off between various characteristics can easily be modeled. Since attractiveness is fully summarized by the subindices I and J, we can define 'iso-attractiveness' profiles, i.e. profiles of observable characteristics that generate the same (distribution of) attractiveness. These are defined, for men, by $i\left(I\left(X_i^1,...,X_i^K\right),\varepsilon_i\right) = C$, where C is a constant, and similarly for women by $j\left(J\left(Y_j^1,...,Y_j^L\right),\eta_j\right) = C'$. Then, assuming I and J to be differentiable, the marginal rate of substitution between characteristics n and m can be defined (for male i) by:

$$MRS_i^{m,n} = \frac{\partial I/\partial X^n}{\partial I/\partial X^m}$$

where the partials are taken at $\left(X_i^1,...,X_i^K\right)$ (and a similar definition can be given for women). From (2), these MRS are given by:

$$\frac{\partial I/\partial X^n}{\partial I/\partial X^m} = \frac{\partial E\left[Y^s \mid X_i^1,...,X_i^K\right]/\partial X^n}{\partial E\left[Y^s \mid X_i^1,...,X_i^K\right]/\partial X^m}, \tag{3}$$

which are exactly identified. Moreover, the left hand side of the expression above does not depend on s, so neither should the right hand side, which generates the overidentifying restrictions we mentioned in the introduction. Conversely, if the right hand side ratio in (3) is independent of s, then there exists a function I, and L functions $\phi_1,...\phi_L$, such that (2) is satisfied, which shows that the condition is also sufficient.

3 Measuring Attractiveness

3.1 Physical Attractiveness

There exists a considerable literature on measuring physical attractiveness in which weight scaled by height (BMI) is widely used as a proxy for socially defined physical attractiveness (e.g., Gregory and Rhum, 2009). Indeed, Rooth (2009) found that photos that were manipulated to make a person of normal weight appear to be obese caused a change in the viewer's perception, from attractive to unattractive.

Both body shape and body size are important determinants of physical attractiveness; in practice, BMI provides information on body size, while the waist-to-hip ratio (WHR) and the waist-to-chest ratio (WCR) provide information on body shape. The available empirical evidence, however, indicates that BMI is a far more important factor than WHR of female physical attractiveness (Toveé, Reinhardt, Emery and Cornelissen, 1998; Toveé et al., 1999). The literature review on body shape, body size and physical attractiveness by Swami (2008) seems to point to BMI being the dominant cue for female physical attractiveness, with WHR (the ratio of the width of the waist to the width of the hips) playing a more minor role. Regarding male physical attractiveness, WCR (waist-to-chest) plays a more important role than either the WHR or BMI, but it must be emphasized that BMI and WCR are strongly positively correlated. Not surprisingly, BMI is correlated with the male attractiveness rating by women, though this correlation is lower than the one with WCR.[1]

Practically, although we would like to have information on BMI for women and WCR for men, we are not aware of any study with detailed measures of body shape and socioeconomic characteristics which simultaneously provides these data for both spouses. Since BMI has been shown to constitute a good proxy for male physical attractiveness, we will use this measure in our analysis.

We conclude with two remarks. First, our notion of attractiveness postulates that individuals of one gender rank the relevant characteristics of the opposite sex in the same way - say, all men prefer thinner women. Such a 'vertical' evaluation may not hold for other characteristics. Age is a typical example: while a female teenager is likely to prefer a male adolescent over a middle age man, a mature woman would probably have the opposite ranking. In this regard, we follow most of the applied literature on matching in assuming that different age classes constitute different matching populations. Since, however, preferences on other characteristics (like BMI) may vary across these populations, we control for age in

[1] Wells, Treleaven and Cole (2007), using a large survey of adults in the UK (more than 4,000 men and more than 5,000 women) and a sophisticated technique to assess body shape (three-dimensional body scanning), investigate the relationship of shape and BMI. They find that BMI conveys different information about men and women: the two main factors associated with weight in men after adjustment for height are chest and waist, whereas in women they are hip and bust. They suggested that chest in men but hips in women reflect physique (the form or structure of a person's body, i.e., physical appearance), whereas waist in men and bust in women reflects fatness.

all our regressions. Secondly, another possible indicator of physical attractiveness, the validity of which has been extensively discussed in the literature (see Herpin (2005) for detailed references), is height. Again, whether the height criterion is valued in a unanimous way (all men prefer taller women) or in an individual-specific one (say, tall men prefer tall women, but short males prefers petites) is not clear and it seems to be a measure of male, rather than female, physical attractiveness. The question, however, can be given an empirical answer that relies on the previous discussion; we consider this issue in section 7.[2]

3.2 Socioeconomic Attractiveness

In our model, men and women observe potential mates' ability in the labor market and in the household, such as ability to generate income, disutility from work, earnings capacity and household productivity. Since most of these are not directly observed by the econometrician, we need to define an acceptable proxy for both genders. The most natural indicator of socioeconomic attractiveness is probably wage; not only does wage directly measure a person's ability to generate income from a given amount of input (labor supply), but it is also strongly correlated with other indicators of socioeconomic attractiveness, such as prestige or social status. The main problem with wage, however, is that it is only observed for people who actually work. This is a relatively minor problem for men, since their participation rate, at least in the age category we shall consider, is close to one; but it may be a serious problem for women. One solution could be to estimate a potential wage for non-working women; the drawback of this strategy being to introduce an additional layer of measurement error in some of the key variables. In practice, however, potential wages are predicted from a small number of variables: age, education, number of children and various interactions of these (plus typically time and geographical dummy variables). Here, we are interested in the matching patterns at first marriage; we therefore consider a female population that is both relatively

[2] Notice also that our analysis refers to the Western culture, as in some developing countries the relationship between female attractiveness and BMI may be different.

homogeneous in age and typically without children. We may therefore assume that education is an acceptable proxy for female socioeconomic attractiveness. Additionally, female education may also capture ability to produce quality household goods, which is likely to be valued by men.

We can now proceed to the empirical analysis of matching patterns along these two dimensions - i.e., physical and socioeconomic attractiveness.

4 Data description

Our empirical work uses data from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal household survey collecting a wide range of individual and household demographic, income, and labor-market variables. In addition, in all the most recent waves since 1999 (1999, 2001, 2003, 2005, and 2007), the PSID provides the weights (in pounds) and heights (in feet and inches) of both household heads and wives, which we use to calculate the BMI of each spouse, defined as an individual's body weight (in kilograms) divided by the square of his or her height (in meters squared)[3]. Oreffice and Quintana-Domeque (2010) has shown that non-response to body size questions appears to be very small in the PSID data. Specifically, item non-response for husband's height is below 1.4% in each year, for wife's height is below 1.4% in each year, and for husband's weight is below 2.2% in each year. Regarding wife's weight, item non-response is below 5.5% in each year.

In each of the survey years under consideration, the PSID comprises about 4,500 married households. We select households with a household head and a wife where both are actually present. In our sample years, all the married heads with spouse present are males, so we refer to each couple as husband and wife, respectively. We confine our study to those couples whose wife is between 20 and 50 years old, given that the median age at first marriage of

[3] The pounds/inches BMI formula is: Weight (in pounds) x 704.5 divided by Height (in inches) x Height (in inches).

women in the US was 25.1 in 2000 and 26.2 in 2008 (U.S. Census Bureau, Current Population Survey, 2005; American Community Survey, 2008). The upper bound 50 is chosen to focus on prime-age couples. Our main analysis comprises white spouses, with the husband working in the labor market, so that we include couples with both working and non-working wives. We focus on white couples because in the PSID blacks are disproportionately over-represented in low-income households ("poverty/SEO sample"). Following Conley and Glauber (2007), we discard those couples whose height and weight values include any extreme ones: a weight of more than 400 or less than 70 pounds, a height above 84 or below 45 inches. In our main analysis we focus on individuals who are in the normal- and over- weight range (18.5$\leq$BMI$<$30). We consider obese individuals in section 7.

Because the PSID main files do not contain any direct question concerning the duration of the marriages, we rely on the "Marital History File: 1985-2007" Supplement of the PSID to obtain the year of marriage and number of marriages, to account for the duration of the couples' current marriage. We merge this information to our main sample using the unique household and person identifiers provided by the PSID. We establish a threshold of less than or equal to three years of marriage, as a proxy for how recently a couple formed. This demographic group is worth analyzing because the marriage market penalties for BMI should arise through sorting at the time of the match.

In the PSID all the variables, including the information on the wife, are reported by the head of the household. Reed and Price (1998) found that family proxy-respondents tend to overestimate heights and underestimate weights of their family members, so that family proxy-respondent estimates follow the same patterns as self-reported estimates (see Gorber et al., 2007, for a review). The authors suggest that the best proxy-respondents are those who are in frequent contact with the target. Since we are considering married couples, the best proxy-respondents are likely to be the spouses. Additionally, although it is well-known that self-reported anthropometric measures are likely to suffer from measurement error, Thomas and Frankenberg (2002) and Ezzati et al. (2006) showed that in the United States, self-reported heights exaggerate actual heights, on average, and that the difference is close to constant for ages 20-50. Finally, Cawley (2000, 2004) used the National Health and Nutrition Examination Survey III (NHANES III) to estimate the relationship between measured height and weight and their self-reported counterparts. First, he estimated regressions of the corresponding measured variable to its self-reported counterpart by age and race. Then, assuming transportability, he used the NHANES III estimated coefficients to adjust the self-reported variables from the NLSY. The results for the effect of BMI on wages were very similar, whether corrected for measurement error or not. Hence, we rely on his findings, and we are confident that our results (based on unadjusted data) are unlikely to be significantly biased.

The additional characteristics we use in our empirical analysis are age, log hourly wage, and education. Education is defined as the number of completed years of schooling and is top-coded at 17 for some completed graduate work. We establish a minimum threshold of 9 years of schooling. State dummy variables are included to capture constant differences in labor and marriage markets across geographical areas in the US. As our analysis concerns several PSID waves, year dummy variables are also used, along with clustering at the head of household level. All our regression analysis is run with bootstrapped standard errors using 1,000 replications based on the number of clusters in household head id (see Cameron and Trivedi, 2009).

5 Matching patterns: a preliminary look

In what follows, we consider two different samples. One consists of the total subpopulation of households satisfying the criteria indicated above, a total of 4,251 observations (approximately 1,750 couples). We shall further restrict our analysis to recently married couples (i.e., couples married for three years of less). From a theoretical perspective, this sample is particularly adequate for studying matching patterns. The price to pay is a serious reduction in the size of the sample, which shrinks to 881 observations (approximately 690 couples).

The main characteristics of the data are described in Table 1. Interestingly, with the exception of age, the main statistics are fairly similar across samples. In each case, the average number of years of schooling slightly exceeds 14, with the recently married couples being little more educated, and the wives being on average more educated than their husbands. Regarding weight, a salient feature is that male BMI is on average much larger than female; the average man is actually overweight (BMI above 25), whereas female average BMI remains inferior to 23 in both samples. When obese spouses are included, the average BMI is 27.63 for husbands and 24.91 for wives. The prevalence of obesity among the husbands is 23%, while for wives it is 15%. These results are in line with those of Kano (2008), Averett et al. (2008) and Oreffice and Quintana-Domeque (2010). These estimates contrast with those of Ogden et al. (2006), who, using data from the NHANES, estimated that the US rate of adult obesity prevalence is 31.1% for males and 33.2% for females in 2003-04. As Kano (2008) pointed out, this difference might stem from the fact that we focus on married couples, not on the general US population.

[**Insert Table 1 about here**]

Regarding the correlation of individual characteristics within couples, Table 2 summarizes some clear patterns. We first note, as expected, a significant level of assortative matching on economic characteristics. In all samples, the wife's education is strongly correlated with both the husband's education ($\rho > .55$) and log wage ($\rho > .2$); these correlations are statistically highly significant, and consistent with previous studies (e.g., Lam, 1988; Wong, 2003). A second conclusion is the existence of a significant negative correlation between education and BMI. The correlation is stronger for women than for men; perhaps more surprising is the fact that, for women, the correlation is the strongest for recently married couples, whereas for husbands the correlation is smaller (in absolute terms) in the recently married sample. An interesting remark, however, is that the correlation between male wage and BMI is actually always positive, and statistically significant in both the total and the recently married samples. Finally, since her education is both positively correlated with his wage but negatively correlated with her BMI, one might expect a negative relationship between his wage and her BMI; Table 2 indeed confirms this prediction in all samples, the correlation ranging between -.09 and -.11 depending on the sample. However, the converse does not hold. Although wealthier husbands tend both to be fatter and to have thinner wives, male and female BMIs are actually *positively* correlated on the sample. This results, which is consistent with previous studies in the medical (e.g., Allison et al., 1996; Speakman et al., 2007) and economic (e.g., Hitsch et al., 2010; Oreffice and Quintana-Domeque, 2010) literatures, suggests that, as argued in introduction, physical appearance is another element of the assortative matching pattern.

[Insert Table 2 about here]

To further explore the relationship between the two aspects - i.e., physical and socioeconomic attractiveness - Tables 3 to 6 split the two samples in two according to each of the various criteria (female education, male wage, male and female BMI). Specifically:

- regarding male wage, the threshold is median log wage; we therefore consider the two subpopulations located respectively below and above the median log wage.
- for female education, we distinguish between women with high school education or less (corresponding to a number of years smaller than or equal to 12) and women with at least some college (13 years and above).
- finally, regarding BMI we follow the literature by distinguishing between "normal" and "overweight" individuals - the threshold being at the value of 25. As discussed above, this results in asymmetries between genders; specifically, two third of males, but only one fourth of females are overweight.

[Insert Tables 3-6 about here]

A first conclusion is that assortative matching indeed takes place along the two dimensions. Starting with the recently married sample, we see (Tables 3 and 4) that high wage husband do have more educated wives, and educated wives have higher wage husbands, in both the normal and the overweight population. This pattern is actually present in the two samples; it simply confirms the assortative matching on socioeconomic characteristics that we mentioned above (and that has been abundantly described in the literature).

Regarding weight, things are a little bit more complex. Recently married wives of overweight husbands tend to have a higher BMI in both the low- and high- wage subsamples; symmetrically, the husbands of overweight wives tend to have a higher BMI in both the low- and high- education subsamples. Note, however, that the difference is not statistically significant, possibly due to the small size of the sample. If we consider the total sample (Tables 5 and 6), the positive BMI correlation is maintained and actually becomes statistically significant, but only among the high wage or high education subpopulations; when the wife education does not exceed high-school, the average weight of the husband is actually lower for overweight wives, although the difference is not statistically significant.

A particularly interesting insight is provided by the *interaction* between these characteristics. Considering, again, the recently married sample (Tables 3 and 4), we see that wives of normal weight husbands are more educated than those of overweight husbands, even within each wage class, and that wives of low-wage husbands tend to have a higher BMI than those of high-wage husbands whether the husband is overweight or not. By the same token, the husband's wage is higher when the wife is normal-weight than when she is overweight, for both high and low female education households. None of these effects is statistically significant at the 5% level, a fact that again may reflect the small size of the sample. If we consider the total sample instead (Tables 5 and 6), we see that again overweight husbands have less educated wives, the difference being now highly significant for the high wage couples (but not for the low wage ones); and that wives of low wage husbands are significantly heavier than those of high wage ones, irrespective of the husband's BMI. Similarly, average husband wage is higher when the wife is not overweight, the difference being (highly) significant for educated women only. Finally, among women who are not overweight, low-educated ones have fatter husbands, the difference being highly significant, although the finding does not extend to (the minority of) overweight women.

All in all, these tables are consistent with the basic story presented above. Assortative matching takes place along the two dimensions of physical and socioeconomic attractiveness; moreover, a trade-off seems to exist, whereby a lower level of physical attractiveness can be compensated by better socioeconomic characteristics and conversely. However, while these findings are globally supportive of our theory, they do not constitute clean tests of it. Developing such tests is the topic of the next section.

6 Formal test and estimation

6.1 A linear specification

In order to formally implement the model, we first need to further specify its form. We start with the benchmark case in which the functions I and J in (1) are linear, similarly to Hitsch et al. (2010):

$$\begin{aligned} I\left(X_i^1, ..., X_i^K\right) &= \sum_k f_k X_i^k \\ J\left(Y_j^1, ..., Y_j^L\right) &= \sum_l g_l Y_j^l \end{aligned}$$

We have concluded above that the distribution of any female characteristic conditional on the husband's profile $\left(X_i^1, ..., X_i^K\right)$ only depends on $I\left(X_i^1, ..., X_i^K\right)$. It follows from (3) that, for any female characteristic s:

$$\frac{\partial E\left[Y_j^s \mid X^1,...,X^K\right]/\partial X^n}{\partial E\left[Y_j^s \mid X^1,...,X^K\right]/\partial X^m}=\frac{f_n}{f_m}$$

and by the same token:

$$\frac{\partial E\left[X_i^s \mid Y^1,...,Y^L\right]/\partial Y^n}{\partial E\left[X_i^s \mid Y^1,...,Y^L\right]/\partial Y^m}=\frac{g_n}{g_m}$$

In other words: if, on the sample of married couples, we regress the various male characteristics over the characteristics of the wife, the coefficients we obtain should be proportional across the various regressions.

In practice, the regression of the kth male attribute over the wife's profile takes the form:

$$X_j^k=\sum_n \gamma_n^k Y_j^n+\eta_j^k \tag{4}$$

where the random term η_j^k captures the impact of the unobserved heterogeneity, as well as other shocks affecting the process; note that we must allow the η_j^k to be correlated across k. The theory then predicts that there exists some $\phi_1,...,\phi_K$ such that:

$$\gamma_n^k=\phi_k\ f_n \text{ for all } (k,n) \tag{5}$$

Equivalently, the γs must be such that:

$$\frac{\gamma_n^k}{\gamma_m^k}=\frac{\gamma_n^s}{\gamma_m^s}=\frac{f_n}{f_m} \text{ for all } (k,s,n,m) \tag{6}$$

Hence, we can estimate (4) simultaneously for all characteristics k using Seemingly-Unrelated-Regression (SUR), and test for (6); alternatively, we can estimate (4) simultaneously for all characteristics k with the restriction (5). If the estimations do not lead to statistically different results, then we obtain the marginal rate of substitution between characteristics n and m from:

$$MRS_i^{m,n} = \frac{f_n}{f_m}$$

Note that, in this linear specification of the indices, the $MRS_i^{m,n}$ does not vary across characteristics k. Finally, the same strategy can be used for female characteristics.

6.2 Main Results

We start with the sample of recently married couples. Table 7 presents the regression of wife's on husband's characteristics. As expected, the wife's BMI is negatively related to the husband's wage and positively to his BMI, while her education exhibits the opposite patterns. This finding is consistent with the view that wage positively contributes to a man's attractiveness, while excess weight has a negative impact. The proportionality test (6) is not rejected (p-value above .35). Table 8 exhibit identical features for a woman's attractiveness, with a very significant correlation of the spouses BMIs, but now a non-significant impact of her education on his BMI, and thus a non-significant ratio (the proportionality test is not rejected with p-value above .30). As discussed above, while the population of recently married couples closely fits our theoretical framework, its small size may be a problem.

[Insert Tables 7-8 about here]

To overcome the sample size issue, we run the same regressions on the total sample; results are reported in Tables 9 and 10. The results are quite encouraging. First, the sign patterns are exactly as before; moreover, all coefficients are significant at the 1% level. Second, the point estimates are in the same ballpark as with the restricted sample, suggesting that the patterns at stake are structural and do not change much over marital duration. Thirdly, the proportionality tests still fail to reject (p-values are larger than .14). All in all, these results support our basic assumption.

[Insert Tables 9-10 about here]

Numerically, the point estimates suggest, for the ratio of the coefficient of husband's log wage to his BMI, a value around -8.5 (or -0.3 if BMI is substituted with its logarithm); in other words, a 10% increase in BMI can be compensated by a 3% increase in husband's wage. A back-of-the-envelope calculation shows that this marginal rate of substitution for men translates into a price per kilo of about 4$ per work week, for a man of an average height earning an average wage who works 40 hours a week. Similarly, the ratio between the wife's education and BMI coefficients is between 2 and 4; i.e., an additional year of education compensates about 3 BMI units - more or less the difference between the average female BMI in the population and one unit above the threshold for being overweight.

We also perform constrained estimations corresponding to the regressions presented above. Tables 11 and 12 present the estimated trade-offs between characteristics for the full sample, which are consistent with the previous unconstrained estimates.

[**Insert Tables 11-12 about here**]

7 Extensions

7.1 Nonlinearities

An obvious weakness of the linear specification adopted so far is that it assumes the MRSs are constant - i.e., that the trade-offs between physical and socioeconomic attractiveness are the same for all agents. We now relax this assumption in different ways. First, we break down the samples by family income, and we perform the same regressions as above on the two subpopulations (below and above the median) thus obtained. The results support the intuition mentioned above. Among low income families, the wife's education is positively related to her husband's wage and negatively to his BMI (both coefficients are significant at the 1% level); the wife's BMI is also significantly and negatively related to the husband's log wage and positively related to his BMI. Among wealthier households, the sign pattern is identical. The interesting finding, however, is that the order of magnitudes across these two subpopulations is similar. The same patterns emerge when considering the regressions of husband's characteristics on the wife's; and we do not find differences in the ratio of coefficients across these two subpopulations. These results suggest that, in a somewhat counterintuitive way, the MRSs between physical and socioeconomic characteristics are quite similar across various income classes.

[**Insert Tables 13-14 about here**]

An alternative and somewhat more structural test consists in enriching the form adopted for the respective indices by introducing an interaction between phsysical and socioeconomic criteria, thus allowing the weight of the physical component of attractiveness to vary with the socioeconomic level. Table 15 confirms the previous conclusions by showing no evidence of interaction effects: the coefficients on the interaction terms are not statistically significant. In Table 16, a similar pattern arises for the husband's log wage regression.

[**Insert Tables 15-16 about here**]

Finally, we have explored other possible deviations from linearity. We have checked for non-monotonicities by adding quartile dummy variables for education, wage and BMI. We did not find any evidence of non-monotonicities. Alternatively, we have run the same regressions using squared terms in education, wage and BMI; again, we did not find evidence of non-linearities.

7.2 Height

Another possible indicator of physical attractiveness is height. However, whether the height criterion is valued in a unanimous way (all men prefer taller women) or in an individual-specific one (say, tall men prefer tall women, but short males prefers petites) is not clear;

moreover, the existing literature tends to suggest that height is a measure of male, rather than female, physical attractiveness.

In Tables 17 and 18, we include this anthropometric dimension as an additional characteristic that men and women may value in the marriage market. Several findings emerge from these estimates. First, accounting for height does not affect our main results. We still cannot reject the proportionality of the ratios between wage (education) and BMI. Second, the only robust relationship regarding height is the correlation between spouses heights; however, height does not significantly correlate with the other indicators (with the exception of husband's weights, which is correlated with the wife's education but not her BMI).

[**Insert Tables 17-18 about here**]

One possible interpretation of these results is that height does not affect the attractiveness index we study. This does not mean that height is irrelevant for the matching process, but simply that it matters, if at all, only as an additional variable (the εs and ηs in our baseline formulation (1)). This interpretation, in turn, suggests a natural test: since the subindices I and J should be weakly separable, we should find that the MRSs between BMI and wage (or education) are the same irrespective of height. In order to test this prediction, we run the previous regressions independently, on subsamples consisting respectively of shorter and taller individuals. The results, as reported in Tables 19-20, are clear: the weak separability property is unambigously not rejected, and the ratios are actually similar in the different subpopulations.

[**Insert Tables 19-20 about here**]

7.3 Obese couples

Our analysis has focused on couples in the normal-overweight range ($18.5 \leq \text{BMI} < 30$). One concern with this population may be the endogeneity of BMI. However, for obese couples, one may think of BMI as being out of their control, given that there are genetic factors that determine obesity status and complex biochemical systems that tend to maintain body weight (Rosenbaum, Leibel and Hirsch, 1997; Comuzzie and Allison, 1998; Woods, Seeley, Porte and Schwarts, 1998). Hence, if we run the regression for obese couples and we find the same substitutability between BMI and wage (or education) as in the sample of normal-overweight couples, then we can argue that the potential endogeneity of BMI over the range normal and overweight is not driving our empirical results. Further, if looking at the sample of obese couples we found the same substitutability as in the sample of normal-overweight couples, this would support our linear framework. Interestingly, Tables 21 and 22 show the similar compensation patterns for obese couples[4].

[**Insert Tables 21-22 about here**]

7.4 Additional issues

Finally, we proceed to a few robustness checks. First, the presentation given above is asymmetric across genders, since the socioeconomic indicator is wage for men and education for women. To see whether this asymmetry may affect our results, we run the regressions using the education of the husband (instead of his wage) to proxy for socioeconomic attractiveness. The qualitative results are similar, although the proportionality of the ratios is now rejected (see Tables 23 and 24).

[**Insert Tables 23-24 about here**]

Secondly, our main results (signs, magnitudes and proportionality) are robust to the inclusion of health status and number of children. This supports the idea that BMI is capturing physical attractiveness rather than health aspects. In the same vein, we have considered alternative BMI ranges such as 20-30 and 17-30, obtaining similar results.

[4] Considering obese and non-obese couples together yields the same qualitative results.

8 Conclusions

Our paper relies on a few, simple ideas. One is that the nature of the matching process taking place on marriage markets is multidimensional, and involves both physical and socioeconomic ingredients. Secondly, we explore the claim that this matching process may admit a one-dimensional representation. In other words, the various characteristics only matter through some one-dimensional index. We present a formal framework in which this assumption can be taken to data. Under a weak separability assumption, we show that our framework generates testable predictions. Moreover, should these predictions be satisfied, then the indices are identified in the ordinal sense (i.e., up to an increasing transform); in particular, the marginal rates of substitution between characteristics, which summarize the trade-offs between the various elements involved, can be recovered. Finally, using data from the PSID, we find that our predictions are not rejected. An estimation of the trade-offs suggests that among men, a 10% increase in BMI can be compensated by a higher wage, the supplement being estimated to be around 3%. Similarly, for women, an additional year of education may compensate up to three BMI units. A back-of-the-envelope calculation shows that this marginal rate of substitution for men translates into a price per kilo of about 4$ per work week, for a man of an average height earning an average wage who works 40 hours a week.

Our approach clearly relies on specific and strong assumptions. One dimensionality is a serious restriction, if only because it assumes that a woman's attractiveness involves the same arguments with identical weighting for all men (and conversely). Still, it can be seen as a first and parsimounious step in a promising direction - i.e., including several dimensions in the empirical analysis of matching. Although we are interested here in marriage markets, other applications (to labor markets in particular) could also be considered. Perhaps the main contribution of this paper is to show that models of this type, once correctly specified, can generate strong testable restrictions, and that the latter do not seem to be obviously counterfactual.

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Table 1: Descriptive Statistics of Main Variables, PSID 1999−2007.							
A. Full Sample	Wife's Age	Husband's Age	Wife's BMI	Husband's BMI	Wife's Education	Husband's Education	Husband's Log Wage
Weighted Mean	37.65	39.78	22.91	25.72	14.13	14.15	3.03
SD	8.20	8.81	2.78	2.39	2.02	2.09	0.63
Min	20	19	18.51	18.55	9	9	1.20
Max	50	69	29.95	29.99	17	17	4.99
Observations	4,251	4,251	4,251	4,251	4,251	4,136	4,251
B. Duration of marriage ≤ 3	Wife's Age	Husband's Age	Wife's BMI	Husband's BMI	Wife's Education	Husband's Education	Husband's Log Wage
Weighted Mean	29.60	31.46	22.68	25.51	14.34	14.12	2.79
SD	6.71	7.50	2.61	2.50	2.00	2.05	0.58
Min	20	19	18.56	18.56	9	9	1.20
Max	50	69	29.95	29.99	17	17	4.99
Observations	881	881	881	881	881	852	881

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50] and education is at least 9 years and is top-coded by the PSID at years 17.

Table 2: Correlation Matrix. Coefficient of correlation (p-value)					
A. Full Sample	Wife's BMI	Husband's BMI	Wife's Education	Husband's Education	Husband's Log Wage
Wife's BMI	1.000				
Husband's BMI	0.0633 (0.0000)	1.000			
Wife's Education	−0.1050 (0.0000)	−0.0885 (0.0000)	1.000		
Husband's Education	−0.1362 (0.0000)	−0.0723 (0.0000)	0.5678 (0.0000)	1.000	
Husband's Log Wage	−0.0907 (0.0000)	0.0306 (0.0460)	0.2736 (0.0000)	0.3492 (0.0000)	1.000
B. Duration of marriage ≤ 3	Wife's BMI	Husband's BMI	Wife's Education	Husband's Education	Husband's Log Wage
Wife's BMI	1.000				
Husband's BMI	0.0572 (0.0895)	1.000			
Wife's Education	−0.1310 (0.0001)	−0.0878 (0.0091)	1.000		
Husband's Education	−0.1948 (0.0000)	−0.0599 (0.0805)	0.5532 (0.0000)	1.000	
Husband's Log Wage	−0.1125 (0.0008)	0.0928 (0.0059)	0.2008 (0.0000)	0.2567 (0.0000)	1.000
Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50].					

Table 3: Mean Wife's Education and BMI by Husband's Weight-Wage pair. Duration of marriage ≤ 3 years.

Wife's Education	Low-Wage Husband	High-Wage Husband	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Husband	14.38 (0.240) 229	15.22 (0.351) 109	*3.92**** *[0.0480]*	*4.78**** *[0.0087]*
Overweight Husband	13.92 (0.171) 343	14.65 (0.240) 200	*6.25*** *[0.0126]*	
F-Test: *Equality of Rows*	*2.60* *[0.1074]*	*1.96* *[0.1624]*	*F-Test:* *Joint Equality of Rows and Columns* *4.54**** *[0.0037]*	
F-Test: *Joint Equality of Rows*	*2.25* *[0.1060]*			

Wife's BMI	Low-Wage Husband	High-Wage Husband	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Husband	22.69 (0.213)	21.73 (0.479)	*3.42** *[0.0650]*	*2.38** *[0.0934]*
Overweight Husband	23.03 (0.205)	22.46 (0.362)	*1.92* *[0.1666]*	
F-Test: *Equality of Rows*	*1.52* *[0.2184]*	*1.66* *[0.1977]*	*F-Test:* *Joint Equality of Rows and Columns* *2.31** *[0.0754]*	
F-Test: *Joint Equality of Rows*	*1.55* *[0.2128]*			

Note:
Means are computed using family weights. Robust standard errors clustered at the household head id are reported in parentheses and p-value of the F-tests in brackets.
Overweight husband takes value 1 if BMI is 25 or above, 0 otherwise.
High-Wage husband takes value 1 if log wage is above the median (in the full sample), 0 otherwise.
The F-tests are performed after estimating the following model:
Wife's Education (BMI) = $\alpha + \beta$Overweight + γHigh-Wage + δ(Overweight×High-Wage)
The F-tests for the equality of rows are Ho: $\alpha = \alpha + \beta$ and Ho: $\alpha + \gamma = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-tests for the equality of columns are Ho: $\alpha = \alpha + \gamma$ and Ho: $\alpha + \beta = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-test for the joint equality of rows and columns satisfies all the previous conditions.

Table 4: Mean Husband's Log Wage and BMI by Wife's Weight-Education pair. Duration of marriage $\leq$ 3 years.

Husband's Log Wage	Low-Educated Wife	High-Educated Wife	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Wife	2.69 (0.058) 176	2.85 (0.041) 539	*5.38*** *[0.0207]*	*2.81** *[0.0612]*
Overweight Wife	2.66 (0.099) 65	2.74 (0.107) 101	*0.31* *[0.5749]*	
F-Test: *Equality of Rows*	*0.07* *[0.7844]*	*1.00* *[0.7844]*	*F-Test:* *Joint Equality of Rows and Columns* *2.39** *[0.0680]*	
F-Test: *Joint Equality of Rows*	*0.54* *[0.5844]*			

Husband's BMI	Low-Educated Wife	High-Educated Wife	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Wife	25.41 (0.300)	25.42 (0.170)	*0.00* *[0.9709]*	*0.03* *[0.9704]*
Overweight Wife	25.83 (0.400)	25.97 (0.397)	*0.06* *[0.8075]*	
F-Test: *Equality of Rows*	*0.77* *[0.3800]*	*1.66* *[0.1980]*	*F-Test:* *Joint Equality of Rows and Columns* *0.82* *[0.4814]*	
F-Test: *Joint Equality of Rows*	*1.22* *[0.2971]*			

Note:
Means are computed using family weights. Robust standard errors clustered at the household head id are reported in parentheses and p-values of the F-tests in brackets.
Overweight wife takes value 1 if BMI is 25 or above, 0 otherwise.
High-Educated wife takes value 1 if education is 13 and above, 0 otherwise.
The F-tests are performed after estimating the following model:
Husband's Log Wage (BMI) = $\alpha + \beta$Overweight + γHigh-Educated + δ(Overweight×High-Educated)
The F-tests for the equality of rows are Ho: $\alpha = \alpha + \beta$ and Ho: $\alpha + \gamma = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-tests for the equality of columns are Ho: $\alpha = \alpha + \gamma$ and Ho: $\alpha + \beta = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-test for the joint equality of rows and columns satisfies all the previous conditions.

Table 5: Mean Wife's Education and BMI by Husband's Weight-Wage pair. Full sample.

Wife's Education	Low-Wage Husband	High-Wage Husband	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Husband	13.78 (0.138) 734	14.83 (0.129) 708	*35.21**** *[0.0000]*	*40.12**** *[0.0000]*
Overweight Husband	13.56 (0.101) 1,332	14.50 (0.100) 1,477	*48.26**** *[0.0000]*	
F-Test: *Equality of Rows*	*1.75* *[0.1865]*	*4.47*** *[0.0346]*	*F-Test:* *Joint Equality of Rows and Columns* *28.79**** *[0.0000]*	
F-Test: *Joint Equality of Rows*	*2.92** *[0.0540]*			

Wife's BMI	Low-Wage Husband	High-Wage Husband	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Husband	23.04 (0.170)	22.41 (0.173)	*7.21**** *[0.0073]*	*5.90**** *[0.0028]*
Overweight Husband	23.20 (0.126)	22.80 (0.130)	*5.35*** *[0.0208]*	
F-Test: *Equality of Rows*	*0.66* *[0.4168]*	*3.55** *[0.0598]*	*F-Test:* *Joint Equality of Rows and Columns* *5.01**** *[0.0018]*	
F-Test: *Joint Equality of Rows*	*2.00* *[0.1360]*			

Note:
Means are computed using family weights. Robust standard errors clustered at the household head id are reported in parentheses and p-values of the F-tests in brackets.
Overweight husband takes value 1 if BMI is 25 or above, 0 otherwise.
High-Wage husband takes value 1 if log wage is above the median, 0 otherwise.
The F-tests are performed after estimating the following model:
Wife's Education (BMI) = $\alpha + \beta$Overweight + γHigh-Wage + δ(Overweight×High-Wage)
The F-tests for the equality of rows are Ho: $\alpha = \alpha + \beta$ and Ho: $\alpha + \gamma = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-tests for the equality of columns are Ho: $\alpha = \alpha + \gamma$ and Ho: $\alpha + \beta = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-test for the joint equality of rows and columns satisfies all the previous conditions.

Table 6: Mean Husband's Log Wage and BMI by Wife's Weight-Education pair. Full sample

Husband's Log Wage	Low-Educated Wife	High-Educated Wife	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Wife	2.85 (0.032) 987	3.15 (0.024) 2,226	*56.50**** *[0.0000]*	*31.36**** *[0.0000]*
Overweight Wife	2.80 (0.046) 408	3.00 (0.048) 630	*9.68**** *[0.0019]*	
F-Test: *Equality of Rows*	*0.96* *[0.3270]*	*7.74**** *[0.0055]*	*F-Test:* *Joint Equality of Rows and Columns* *25.92**** *[0.0000]*	
F-Test: *Joint Equality of Rows*	*4.35*** *[0.0131]*			
Husband's BMI	Low-Educated Wife	High-Educated Wife	*F-Test: Equality of Columns*	*F-Test: Joint Equality of Columns*
Normal Weight Wife	25.98 (0.139)	25.52 (0.095)	*7.75**** *[0.0054]*	*4.36*** *[0.0129]*
Overweight Wife	25.80 (0.195)	25.98 (0.172)	*0.47* *[0.4913]*	
F-Test: *Equality of Rows*	*0.65* *[0.4200]*	*6.01*** *[0.0144]*	*F-Test:* *Joint Equality of Rows and Columns* *3.72*** *[0.0110]*	
F-Test: *Joint Equality of Rows*	*3.33*** *[0.0359]*			

Note:
Means are computed using family weights. Robust standard errors clustered at the household head id are reported in parentheses and p-value of the F-tests in brackets.
Overweight wife takes value 1 if BMI is 25 or above, 0 otherwise.
High-Educated wife takes value 1 if education is 13 and above, 0 otherwise.
The F-tests are performed after estimating the following model:
Husband's Log Wage (BMI) = $\alpha + \beta$Overweight + γHigh-Educated + δ(Overweight×High-Educated)
The F-tests for the equality of rows are Ho: $\alpha = \alpha + \beta$ and Ho: $\alpha + \gamma = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-tests for the equality of columns are Ho: $\alpha = \alpha + \gamma$ and Ho: $\alpha + \beta = \alpha + \beta + \gamma + \delta$, respectively. The F-test for the joint equality of rows is Ho: $\alpha = \alpha + \beta$ and $\alpha + \gamma = \alpha + \beta + \gamma + \delta$. The F-test for the joint equality of rows and columns satisfies all the previous conditions.

Table 7: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Duration of marriage ≤ 3 years.

	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.637*** (0.174)	0.661*** (0.128)
Husband's BMI	0.132*** (0.039)	−0.075** (0.031)
Wife's Age	0.008 (0.017)	0.016 (0.012)
R^2	0.10	0.17
Sample size	881	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−4.82*** (1.82)	−8.84** (3.99)
Equality of ratios test	$Chi^2(1) = 0.87$ (p-value = 0.3515)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 687 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 8: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Duration of marriage ≤ 3 years.

	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.083 (0.052)	0.048*** (0.010)
Wife's BMI	0.094*** (0.034)	−0.023*** (0.007)
Husband's Age	0.037*** (0.012)	0.020*** (0.003)
R^2	0.13	0.23
Sample size	881	
B. MRS = ratio of coefficients		
$\frac{\text{Wife's Education}}{\text{Wife's BMI}}$	−0.884 (0.696)	−2.06** (0.850)
Equality of ratios test	$Chi^2(1) = 1.04$ (p-value = 0.3080)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 687 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 9: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Full sample.		
	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.543*** (0.094)	0.852*** (0.073)
Husband's BMI	0.086*** (0.026)	−0.079*** (0.019)
Wife's Age	0.034*** (0.008)	−0.016*** (0.006)
R^2	0.05	0.14
Sample size	4,251	
B. MRS = ratio of coefficients		
$\frac{\text{Husband's Log Wage}}{\text{Husband's BMI}}$	−6.31*** (2.18)	−10.78*** (2.76)
Equality of ratios test	$Chi^2(1) = 1.86$ (p-value = 0.1726)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 10: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Full sample.

	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.095*** (0.029)	0.073*** (0.007)
Wife's BMI	0.051*** (0.019)	−0.018*** (0.004)
Husband's Age	0.023*** (0.006)	0.017*** (0.001)
R^2	0.04	0.20
Sample size	4,251	
B. MRS = ratio of coefficients		
Wife's Education / Wife's BMI	−1.86** (0.933)	−4.09*** (1.13)
Equality of ratios test	$Chi^2(1) = 2.17$ (p-value = 0.1411)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 11: Constrained SUR Regressions of Wife's Characteristics on Husband's Characteristics. Full sample.

Wife's BMI = {a1} + {k}×{b2}×Husband's Log Wage + {b2}×Husband's BMI + {d1}×Wife's Age
Wife's Education = {a2} + {k}×{c2}×Husband's Log Wage + {c2}×Husband's BMI + {d2}×Wife's Age

	Wife's BMI	Wife's Education
Index's coefficients		
{k}	−11.65*** (3.78)	
{b2}	0.050*** (0.015)	--
{c2}	--	−0.082*** (0.019)
{d1}	0.033*** (0.008)	--
{d2}	--	−0.016*** (0.006)
R^2	0.02	0.09
Sample size	4,251	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Feasible generalized non-linear least squares regression estimates. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 12: Constrained SUR Regressions of Husband's Characteristics on Wife's Characteristics. Full sample.

Husband's BMI = {a1} + {k}×{b2}×Wife's Education + {b2}×Wife's BMI + {d1}×Husband's Age
Husband's Log Wage = {a2} + {k}×{c2}×Wife's Education + {c2}×Wife's BMI + {d2}×Husband's Age

	Husband's BMI	Husband's Log Wage
Index's coefficients		
{k}	−4.20*** (1.30)	
{b2}	0.023*** (0.009)	--
{c2}	--	−0.020*** (0.004)
{d1}	0.023*** (0.006)	--
{d2}	--	0.018*** (0.001)
R^2	0.02	0.14
Sample size	4,251	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Feasible generalized non-linear least squares regression estimates. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 13: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Full sample broken down by Family Income (below and above the median).

I. Low Family Income	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.480*** (0.159)	0.405*** (0.120)
Husband's BMI	0.065* (0.035)	−0.070*** (0.025)
Wife's Age	0.032*** (0.010)	−0.021*** (0.008)
R^2	0.07	0.10
Sample size	2,126	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−7.36 (4.61)	−5.79** (2.64)
Equality of ratios test	$Chi^2(1) = 0.09$ (p-value = 0.7639)	
II. High Family Income	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.361*** (0.140)	0.456*** (0.101)
Husband's BMI	0.110*** (0.037)	−0.077*** (0.025)
Wife's Age	0.038*** (0.010)	−0.028*** (0.008)
R^2	0.08	0.11
Sample size	2,125	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−3.28** (1.65)	−5.94*** (2.33)
Equality of ratios test	$Chi^2(1) = 0.95$ (p-value = 0.3298)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,099 (low income) and 1,030 (high income) clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 14: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Full sample broken down by Family Income (below and above the median).

I. Low Family Income	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.106** (0.043)	0.020*** (0.007)
Wife's BMI	0.038 (0.028)	−0.011*** (0.004)
Husband's Age	0.016** (0.008)	0.006*** (0.001)
R^2	0.06	0.09
Sample size	2,126	
B. MRS = ratio of coefficients		
Wife's Education / Wife's BMI	−2.79 (2.46)	−1.74* (1.01)
Equality of ratios test	$Chi^2(1) = 0.15$ (p-value = 0.6979)	
II. High Family Income	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.100*** (0.037)	0.038*** (0.009)
Wife's BMI	0.072*** (0.027)	−0.011* (0.006)
Husband's Age	0.019** (0.009)	0.009*** (0.002)
R^2	0.06	0.10
Sample size	2,125	
B. MRS = ratio of coefficients		
Wife's Education / Wife's BMI	−1.40*** (0.756)	−3.44* (2.08)
Equality of ratios test	$Chi^2(1) = 0.85$ (p-value = 0.3552)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,099 (low income) and 1,030 (high income) clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 15: SUR Regressions of Wife's Characteristics on Husband's Characteristics with interaction term. Full sample.

Wife's BMI = {A1} + {B1}×Husband's Log Wage + {B2}×Husband's BMI + {B3}×Husband's BMI ×Husband's Log Wage + {D1}×Wife's Age

Wife's Education = {A2} + {C1}×Husband's Log Wage + {C2}×Husband's BMI + {C3}×Husband's BMI ×Husband's Log Wage + {D2}×Wife's Age

	Wife's BMI	Wife's Education
Index's coefficients		
{B1}	−1.82* (1.01)	--
{B2}	−0.065 (0.120)	--
{B3}	0.050 (0.039)	--
{D1}	0.031*** (0.008)	--
{C1}	--	1.42** (0.682)
{C2}	--	−0.020 (0.082)
{C3}	--	−0.018 (0.026)
{D2}	--	−0.016*** (0.006)
R^2	0.02	0.09
Sample size	4,251	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Feasible generalized non-linear least squares regression estimates. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 16: SUR Regressions of Husband's Characteristics on Wife's Characteristics with interaction term. Full sample.

Husband's BMI = {A1} + {B1}×Wife's Education + {B2}×Wife's BMI + {B3}×Wife's BMI ×Wife's Education + {D1}×Husband's Age

Husband's Log Wage = {A2} + {C1}×Wife's Education + {C2}×Wife's BMI + {C3}×Wife's BMI ×Wife's Education + {D2}×Husband's Age

	Husband's BMI	Husband's Log Wage
Index's coefficients		
{B1}	−0.626*** (0.220)	--
{B2}	−0.281** (0.135)	--
{B3}	0.024** (0.009)	--
{D1}	0.023*** (0.006)	--
{C1}	--	0.074 (0.051)
{C2}	--	−0.024 (0.030)
{C3}	--	0.001 (0.002)
{D2}	--	0.018*** (0.001)
R^2	0.02	0.14
Sample size	4,251	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Feasible generalized non-linear least squares regression estimates. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 17: SUR Regressions of Wife's Characteristics on Husband's Characteristics adding height. Full sample.

	Wife's BMI	Wife's Height	Wife's Education
A. Index's coefficients on			
Husband's Log Wage	−0.540*** (0.094)	−0.010 (0.104)	0.832*** (0.073)
Husband's BMI	0.086*** (0.026)	0.035 (0.028)	−0.077*** (0.019)
Husband's Height	−0.009 (0.024)	0.150*** (0.027)	0.055*** (0.018)
Wife's Age	0.033*** (0.008)	−0.019** (0.008)	−0.015*** (0.006)
R^2	0.05	0.08	0.15
Sample size	4,251		
B. MRS = ratio of coefficients			
$\frac{\text{Husband's Log Wage}}{\text{Husband's BMI}}$	−6.30*** (2.19)	−0.29 (2.97)	−10.80*** (2.83)
Test ratio column (1) = column (2)	$Chi^2(1) = 2.57$ (p-value = 0.1090)		
Test ratio column (1) = column (3)	$Chi^2(1) = 1.81$ (p-value = 0.1787)		
Test ratio column (2) = column (3)	$Chi^2(1) = 6.67$ (p-value = 0.0098)		

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 18: SUR Regressions of Husband's Characteristics on Wife's Characteristics adding height. Full sample.

	Husband's BMI	Husband's Height	Husband's Log Wage
A. Index's coefficients on			
Wife's Education	−0.098*** (0.029)	0.119*** (0.036)	0.072*** (0.007)
Wife's BMI	0.053*** (0.019)	0.004 (0.022)	−0.018*** (0.004)
Wife's Height	0.034 (0.023)	0.149*** (0.029)	0.012** (0.005)
Husband's Age	0.023*** (0.006)	−0.016** (0.007)	0.018*** (0.001)
R^2	0.04	0.08	0.21
Sample size	4,251		
B. MRS = ratio of coefficients			
Wife's Education / Wife's BMI	−1.83** (0.88)	27.20 (136.5)	−4.02*** (1.11)
Test ratio column (1) = column (2)	$Chi^2(1) = 0.05$ (p-value = 0.8316)		
Test ratio column (1) = column (3)	$Chi^2(1) = 2.20$ (p-value = 0.1376)		
Test ratio column (2) = column (3)	$Chi^2(1) = 0.05$ (p-value = 0.8191)		

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,749 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 19: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Full sample broken down by Husband's Height (below and above the median).		
I. Short Husbands	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.509*** (0.140)	0.673*** (0.106)
Husband's BMI	0.084** (0.041)	−0.097*** (0.029)
Wife's Age	0.016 (0.011)	0.003 (0.009)
R^2	0.09	0.16
Sample size	1,810	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−6.07* (3.32)	−6.95*** (2.35)
Equality of ratios test	$Chi^2(1) = 0.05$ (p-value = 0.8289)	
II. Tall Husbands	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−0.597*** (0.131)	0.961*** (0.098)
Husband's BMI	0.089*** (0.031)	−0.067*** (0.024)
Wife's Age	0.047*** (0.010)	−0.029*** (0.008)
R^2	0.07	0.18
Sample size	2,441	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−6.73** (2.76)	−14.45*** (5.61)
Equality of ratios test	$Chi^2(1) = 1.60$ (p-value = 0.2056)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 809 (short husbands) and 1,070 (tall husbands) clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 20: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Full sample broken down by Wife's Height (below and above the median).

I. Short Wives	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.050 (0.044)	0.079*** (0.010)
Wife's BMI	0.053* (0.032)	−0.020*** (0.006)
Husband's Age	0.027*** (0.009)	0.017*** (0.002)
R^2	0.06	0.22
Sample size	1,798	
B. MRS = ratio of coefficients		
Wife's Education / Wife's BMI	−0.938 (1.05)	−3.96*** (1.45)
Equality of ratios test	$Chi^2(1) = 2.72$ (p-value = 0.0992)	
II. Tall Wives	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.138*** (0.040)	0.067*** (0.009)
Wife's BMI	0.054** (0.023)	−0.017*** (0.006)
Husband's Age	0.021*** (0.008)	0.018*** (0.002)
R^2	0.07	0.22
Sample size	2,453	
B. MRS = ratio of coefficients		
Wife's Education / Wife's BMI	−2.55* (1.36)	−3.99*** (1.54)
Equality of ratios test	$Chi^2(1) = 0.47$ (p-value = 0.4953)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 801 (short wives) and 1,084 (tall wives) clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 21: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Obese couples.		
	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Log Wage	−3.19*** (0.642)	0.718*** (0.214)
Husband's BMI	0.127* (0.071)	−0.047** (0.020)
Wife's Age	0.062 (0.042)	−0.035*** (0.013)
R^2	0.20	0.23
Sample size	525	
B. MRS = ratio of coefficients		
$\frac{\text{Husband's Log Wage}}{\text{Husband's BMI}}$	−25.12 (15.74)	−15.20* (7.96)
Equality of ratios test	$Chi^2(1) = 0.36$ (p-value = 0.5469)	

Note: We consider obese couples, BMI ≥30. Wife's age is in the range [20, 50]. Standard errors are reported in parentheses. Bootstrapped standard errors (1,000 replications based on 263 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 22: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Obese couples.		
	Husband's BMI	Husband's Log Wage
A. Index's coefficients on		
Wife's Education	−0.324** (0.150)	0.045*** (0.016)
Wife's BMI	0.086* (0.050)	−0.021*** (0.004)
Husband's Age	−0.007 (0.037)	0.017*** (0.003)
R^2	0.23	0.33
Sample size	525	
B. MRS = ratio of coefficients		
$\frac{\text{Wife's Education}}{\text{Wife's BMI}}$	−3.78 (3.06)	−2.20** (0.99)
Equality of ratios test	$Chi^2(1) = 0.27$ (p-value = 0.6026)	

Note: We consider obese couples, BMI ≥30. Wife's age is in the range [20, 50]. Standard errors are reported in parentheses. Bootstrapped standard errors (1,000 replications based on 263 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 23: SUR Regressions of Wife's Characteristics on Husband's Characteristics. Full sample. Husband's Education instead of Husband's Log Wage.		
	Wife's BMI	Wife's Education
A. Index's coefficients on		
Husband's Education	−0.192*** (0.032)	0.524*** (0.023)
Husband's BMI	0.070*** (0.027)	−0.041** (0.018)
Wife's Age	0.024*** (0.007)	−0.007 (0.005)
R^2	0.07	0.35
Sample size	4,136	
B. MRS = ratio of coefficients		
Husband's Log Wage / Husband's BMI	−2.76** (1.20)	−12.92** (5.70)
Equality of ratios test	$Chi^2(1) = 3.11$ (p-value = 0.0779)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,707 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1

Table 24: SUR Regressions of Husband's Characteristics on Wife's Characteristics. Full sample. Husband's Education instead of Husband's Log Wage.

	Husband's BMI	Husband's Education
A. Index's coefficients on		
Wife's Education	−0.096*** (0.031)	0.553*** (0.024)
Wife's BMI	0.051** (0.020)	−0.060*** (0.015)
Husband's Age	0.024*** (0.006)	0.019*** (0.005)
R^2	0.04	0.37
Sample size	4,136	
B. MRS = ratio of coefficients		
$\frac{\text{Wife's Education}}{\text{Wife's BMI}}$	−1.88* (1.02)	−9.16*** (2.40)
Equality of ratios test	$Chi^2(1) = 7.87$ (p-value = 0.0050)	

Note: We consider individuals who are in the normal-overweight range, BMI [18.5, 30). Wife's age is in the range [20, 50]. Bootstrapped standard errors (1,000 replications based on 1,707 clusters in household head id) are reported in parentheses. All regressions include state and year fixed effects.
*** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1