

Bright and Wealthy: Exploring Assortative Mating in Italy

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Abstract

While current literature on marital sorting focuses alternatively on the role of schooling or on the role of wages, we argue that both variables simultaneously determine the level of assortative mating, since schooling and wages are never perfectly correlated. Using data from the Bank of Italy's Survey on Household Income and Wealth (SHIW), with families tracked longitudinally from 1989 to 2004, we estimate a system of simultaneous mating equations for wages and schooling. We find evidence that cross-effects of these variables account for between 4,6% and 7,3%.

1 Introduction

In a monogamous marriage market, assortative mating is the pattern of traits' pairings observed between partners. In his first work on marriage markets, Becker (1973) noted that sorting between traits of married couples is not a random phenomenon. People prefer to match according to personal characteristics, like age, beauty, wages, education. Assortative mating can either be negative or positive. For example, assume that in the marriage market the only relevant

trait in pairing is labor productivity: under *positive* assortative mating couples will be formed by individuals endowed with similar productivity, while under *negative* assortative mating will be formed by spouses' whose productivity in labor activities tend to be different¹. When positive assortative mating prevails, the correlation between the spouses' productivity displays a positive sign.

When it comes to matching on more than a single variable, interpreting cross correlations becomes remarkably trickier. Since the work of Benham (1974), the positive empirical relationship between spousal education and one's earnings has become a focal point for applied research in family economics (Boulier and Rosenzweig, 1984). Given a high degree of educational mating in the marriage market, a simple OLS regression of the effect of spousal education on wages – no matter how many controls are introduced by the statistician – cannot reveal a causation, since the estimated coefficient could merely capture a systematic tendency toward marrying the likes. According to game theory (Roth

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¹The observed degree of assortative mating depends also on the marginal distribution of traits in the two sides of the market, since a given degree of assortative mating is always observed in the data because of random matching. Using marriage-market-level data, it is possible to disentangle random and systematic sorting. See Sundaram (2004) and Liu and Lu (2006).

and Sotomayor, 1990; Gusfield and Irving, 1989; Knuth, 1997 [1981]; Gale and Shapley, 1962), the outcome of the marriage market mechanism is such that more educated members of one sex tend to marry more educated members of the other sex: the observed cross correlations are simply a by-product of mating on education. However, it may well be that spousal education helps partners accumulating human capital and increasing earnings, since couples with high levels of education are more likely to share ideas, values, and tastes within the family and this homogeneity may impact positively also upon market productive traits (Huang, Li, Liu, and Zhang, 2006).

Whereas the cross-productivity hypothesis has some straightforward implications for spousal earnings, the implications of the selective-mating hypothesis are not so clear-cut. The problems here are similar to those faced in the human capital literature with regard to alternative explanations for the positive correlation between schooling and earnings i.e., a problem of mutual causation. Higher education could either signal high skilled individuals (Spence, 1973) or a deliberate attempt to increase the level of human capital (Becker, 1964): in this context of multiple causality, devising a test to disentangle the relative importance of selectivity from that of cross-productivity is still an open issue, since finding genuinely exogenous variables is far from simple in this context.

We enter this debate pointing out that, prior to cross-effects, also the level of sorting between spouses adjusts to schooling and labor conditions. Our approach explicitly takes into account that the marriage market jointly determines assortative mating on schooling *and* on wages, i.e., market and household productivity, because schooling and wages are partly substitutable in the marriage market, as emphasized by the theory of compensating differentials in marriage (Grossbard-Shechtman and Neuman, 1988). Accordingly, we adopt the methodology

of simultaneous estimation for two equations: educational mating and wage mating, under the assumption that both decisions are strongly related. The model is estimated for the Italian marriage market in which schooling and market productivity are important traits which *jointly* contribute to the process of marital sorting. Assuming that prospective partners have rational expectations and private information on each other that can be revealed only gradually across time, we estimate a non-recursive system of equations which allows to appreciate how marriage markets work. The data are extracted from the Bank of Italy's Survey on Household Income and Wealth (SHIW), with families tracked longitudinally from 1989 to 2004. The temporal structure of the dataset permits an estimation of long-run performances in the job market and in the educational system which cannot be fully disclosed at the beginning of marriage, but whose expected value is relevant for spouse's selection. Our key finding indicates that wage has predictive power in forecasting educational mating and that education also helps predicting wage sorting. The inclusion of these cross variables significantly decreases the level of observed correlations: these cross effects account from 4,6% to 7,3%.

The next section of this article is devoted to surveying the literature on cross-effects of wage and schooling between partners. Then, we introduce a stylized model of the marriage market which can account for multidimensional sorting. Various estimates for the model are provided and the resulting evidence is discussed, along with possible directions for further research.

2 Background Literature

The phenomenon of spousal matching over personal traits has a long research tradition in the fields of biology, economics, and sociology. Ep-

stein and Guttman (1984), in one of the most extensive study on this topic to date, observe positive assortative mating for ages, wages, education, religion, heights, IQ scores, and ethnicity. As noted earlier, the applied economic literature on the cross-effects of education dates back to the work of Benham (1974) who finds that wife's education increases husband's wage by 3% in the US. According to Tiefenthaler (1997), wife's education increases husband's wage by 5–7% in Brazil, while husband's education increases wife's wage by roughly 5%, though the estimation does not explicitly control for assortative mating. Also, significant benefits are found to arise from role specialization in the family and association, i.e., working in the same market sector. In their study on Chinese twins, controlling for selectivity in the marriage market and for family background, Huang, Li, Liu, and Zhang (2006) find that husband's education increases wife's earnings by 3.5%, but cannot find any significant effect running in the opposite direction. They provide evidence that the increase in wife's earnings is explained by a positive effect on hourly wage.

Empirical results universally show a positive sign for the correlation between spouses' wages. In their study of assortative mating, Zhang and Liu (2003) discover that wives' schooling impacts positively on her husband's wage, but a similar effect does not work the other way around. Their major finding is that the correlation between potential wages is statistically non significant, so that the main gains from marriage derive from role specialization, as in Becker (1991 [1981]). This evidence is partly consistent with the work of Smith (1979) who comes across low correlation levels between wage residuals once the estimation procedure takes into account sample selection. To date, the only result of negative assortative mating on wages has been obtained by Zimmer (1996) with a negative coefficient for North-American blacks, even though Becker (1991 [1981], pp. 118–119) cites unpublished

negative coefficients obtained by Gregg Lewis. Grossbard-Shechtman and Neuman (1991), using the 20% sample from 1983 Census of Israel, find evidence of reciprocal influence of spouses' levels of schooling and significant complementarities in earnings-related measures. Hours of work have also received interest within this research field: Pencavel (1998) tests whether the market work hours of husbands and wives are correlated with their spouses' schooling levels. Using the 1990 Census for US, he finds that husbands are little influenced by their wives schooling, while women married to a college-educated man work 4% fewer market hours than women married to high-school dropouts, and the effect is almost doubled when the couple has children aged less than six years. This suggests that college-educated husbands substitute some of their own hours of work with their wives' hours in the market.

Another stream of literature makes explicit that the process of mating involves variables which the researcher can hardly fully control for. In this perspective, unobserved components of educational and income mating are employed to infer about the systematic patterns of marriage. Rupert and Cornwell (1997) find weak evidence of cross-productive effects in marriage: according to their estimation based on the National Longitudinal Survey of Young Men, the marriage premium – the observed positive difference in the wage level between married and unmarried men – is attributable to unobservable individual effects that are correlated with marital status and wages. Nakosteen and Zimmer (2001), using unobservable components of hourly wages observed before and immediately after marriage, find evidence of positive assortative mating on the basis of earnings for the subjects observed in the Panel Study of Income Dynamics (PSID). Behrman, Birdsall, and Deolalikar (1995) employ an educational mating equation to estimate unobservable skills which are found to impact significantly on the wage

of Indian husbands. In their recent contribution, Brynin and Francesconi (2004) have extended the same econometric methodology to wives and found several measures of market success associated with unobservable components of human capital.

In contrast to previous literature, this article argues that marital sorting operates not only along the educational dimension but also on the income dimension. However, since education and labor income are not perfectly correlated, *both* correlations need to be taken into account when studying marital sorting. In this perspective, we contribute to clarify the missing link in the applied literature between the job market and the marriage market, a point which has recently received attention in a theoretical article by Chiappori, Iyigun, and Weiss (2006). As of today, a joint estimation of market productivity *and* educational sorting for married couples has not been attempted yet and will be the theme of the next sections.

3 The Marriage Market

The marriage market model presented here is based on the assumption that schooling produces monetary effects because more educated people usually have better jobs, obtain higher salaries on the job market, and have greater chances of moving upward socially (Kalmijn, 1994). Non-monetary effects also follow from schooling, since education generally provides broader perspectives on world visions and relaxes strictness from inherited cultural values. Married individuals can gain from a higher level of their spouses' education because of the monetary and the non-monetary benefits from schooling: couples in which both spouses share the same background values enjoy higher utility from the production of public household goods. In an ideal setting in which schooling and wages are perfectly correlated, and no significant heterogeneity exists

between people, the same marital sorting would prevail with regard to education and to wages, since the choice variable would make no difference.

In contrast, the real world is characterized by imperfect correlations between schooling and wages: this impacts the labor market as well as the marriage market. Explanations for the imperfect correlation in the labor market are not particularly relevant, since here we focus on what happens in the marriage market and on the heterogeneity observed inside and among the couples. This heterogeneity in sorting patterns is mainly due to: (1) different personal tastes toward the monetary and the non-monetary benefit which follow from education, and (2) unobservable factors which the social scientist can hardly control for.

Assuming that utility is transferable between partners, as in the classical Becker's model, partners can make themselves attractive compensating a low level of a personal trait with a high level of another valuable personal trait. After marriage, this compensation can take the form of monetary transfers, like in the model of Grossbard-Shechtman and Neuman (1988), but to a certain extent this compensation of traits can take place also in the marriage market: for example, a prospective husband endowed with low market productivity could make himself more attractive when endowed with relatively higher education. If this holds true, schooling and income are partly substitutable in women's eyes. As a result, marital sorting happens not only along the educational dimension, but partly also on the income dimension. Dual matching – with regard to education and job prospects – and simultaneity are the cornerstones of the present model. We also assume that, when people meet in the marriage market, they form expectations on each other's chances to obtain education and wage. Obviously, any family can benefit from high levels of wage and from high levels of education, but imperfect cor-

relation and personal tastes introduce the possibility of substitution between the two inputs of household production.

Formally, actual household production for a generic family can be written as:

$$F = F(\mathbf{v}) \quad (1)$$

where F is the total value of household-produced goods,

$$\mathbf{v} \equiv [e_w \ e_b \ s_w \ s_b]'$$
 (2)

is a vector containing the levels of education (e) and the levels of wages (s) of the wife (w) and of the husband (b). F is assumed to be increasing in the level of each observable independent variable. Further, assuming competition among women and among men to marry the best partners, the marriage market mechanism maximizes the sum of the expected value of (1) across all possible matches (Becker, 1991 [1981], pp. 82–84).

Competition in the marriage market is based on the assumption that matching is not completely random. Then, the possibility of marrying a man of a given educational level depends, among other things, upon a person's educational and wage levels. This systematic relation between one's traits and his/her partner's is termed *mating function* and has been introduced in the context of family economics by Boulier and Rosenzweig (1984). While current literature on human capital (Brynin and Francesconi, 2004; Behrman, Birdsall, and Deolalikar, 1995) estimates mating functions only with regard to schooling, we allow for simultaneous determination of educational and income sorting. Finally, to enable simultaneous estimation of mating equations, we With all the assumptions previously stated, the resulting mating equation system can be written as follows:

$$\mathbf{D} \mathbf{v} + \mathbf{X}' \boldsymbol{\beta} + \boldsymbol{\Omega} = 0 \quad (3)$$

where

$$\mathbf{D} \equiv \begin{bmatrix} 1 & -d_1 & 0 & -d_2 \\ -d_3 & 1 & d_4 & 0 \\ 0 & -d_5 & 1 & -d_6 \\ -d_7 & 0 & -d_8 & 1 \end{bmatrix} \quad (4)$$

is the matrix of coefficients for the endogenous variables, \mathbf{X} is a matrix of exogenous variables, $\boldsymbol{\beta}$ is a vector of estimated parameters for the exogenous variables, and

$$\boldsymbol{\Omega} \equiv [\omega_w^e \ \omega_b^e \ \omega_w^s \ \omega_b^s]'$$
 (5)

is a vector of i.i.d. error terms.

To make things clearer, let us consider the mating equations for wife's education and wage. These can be written as:

$$e_w = d_1 e_b + d_2 s_b + \mathbf{x}_b^e \boldsymbol{\beta}_b^e + \omega_w^e \quad (6)$$

$$s_w = d_5 e_b + d_6 s_b + \mathbf{x}_b^s \boldsymbol{\beta}_b^s + \omega_w^s \quad (7)$$

where the terms for the exogenous characteristics \mathbf{x} are allowed to vary across equations. The hypotheses that

$$d_1 > 0 \quad (8)$$

$$d_6 > 0 \quad (9)$$

have been tested in the literature under the assumption that $d_2 = d_5 = 0$ and found true. Instead, we are interested in testing whether

$$d_1, d_2 > 0 \quad (10)$$

$$d_6, d_5 > 0 \quad (11)$$

i.e., if there is any possibility of trade between schooling and market productivity. To sum up, this structure for marital mating is based on four equations: two for schooling of husband and wives and two more for wages of the same spouses. Each mating equation implies that wage and schooling of a man jointly determine the expected levels of schooling and of wage of his prospective wife and the same causal relation

holds true also for women. This implies the possibility that education and wage can impact differently prospective spouse's wage and schooling; furthermore, those effects need not to be symmetric with regard to gender and can provide interesting sources of imbalances in the marriage market. In statistical terms, we are interested in testing the positive signs for the coefficients in the D matrix.

4 Estimation and Data

4.1 The Dataset

The data used for estimation originate from the Bank of Italy's Survey on Household Income and Wealth (SHIW) sample, containing observations on families and individual components tracked longitudinally from 1989 to 2004. Though SHIW's data collection actually dates back to 1977, it is only from 1989 that data on education are collected also for nonworking individuals. Apart from observations from 1977 to 1987, other groups were dropped: (1) couples for which education is missing, (2) couples for which job status is missing, (3) couples in which spouses are retired, (4) couples in which husbands are older than 65 and wives are older than 60. As a result of this process of selection, the sample reduces to 18,459 couples. All income and wealth measures are adjusted to 2004-equivalent euros. Education and wages are in logarithms, with the censoring point for wage (originally set equal to zero) being shifted by one euro to obtain non-missing values for predicted wages also in case of individuals who do not work. In our sample, the percentage of wives working and receiving a salary is 43%, while the proportion of husbands is 91%. According to these figures, the problem of censoring for wives is particularly acute, so it is tackled from the beginning, performing a Heckman estimation over the subsamples of wives and husbands and using the resulting equations to predict notional

wages for the censored observations, as described in Cahuc and Zylberberg (2004, p. 34–35). Results are reported in tables 3 and 4, with further details provided in the estimation section of this paper.

To check the basic relations between the variables of interest, i.e., wages and schooling, pairwise correlations on the censored sample are tabulated in table 1 and contrasted with the coefficients calculated over the uncensored sample, reported in table 2. Correlation between spouses' schooling is around 64%, a value which is fairly higher than the average 50% as reported by Lam (1988) for the US, while correlation between wages goes from 41% in the censored sample to 29,7% in the uncensored sample². Also, we employ the method of quantile regressions, as described in Koenker (2005), since we are interested not only in the strength of the linear relation around the mean, but also in what is happening in other sections of the distribution of the dependent variable. Graph 1 shows the relation between the log of husband's years of schooling on his wife's years of schooling. On the x -axis we have the quantiles of the dependent variable and on the y -axis the value of the estimated coefficients. The straight line is the value of the OLS estimator, being used as a benchmark, surrounded by confidence bands at 95%. The kinked line, surrounded by grey-shaded confidence bands, shows the values of quantile regression coefficients obtained at different points of the distribution of the dependent variable. The awkward shape of this particular curve is due to the discrete nature of the data on schooling, which are available only for classes of completed education levels. The resulting reciprocal elasticity ranges from 35% in the highest quantile to 100% in the 30-60% quantiles.

Graph 2 displays the relation between the log of husband's wage and wife's wage, provided that

²For more details on the structure of mating in Italy see Filoso (2007).

both work in the marketplace. Conditioning on husbands' wage quantiles, the strength of the linear relation between the two variables displays a non-linear trend, with steadily decreasing values until the last quantiles, where the relation is jumping back to the same values observed for the low-wage wives. Correcting for selectivity restores a U-shaped curve between the two wages, as it is evident from graph 3.

Lastly, graphs from 4 to 7 show the elasticity between schooling and wage, for husbands and wives, in the case of censoring and in the case of imputed potential wages to nonworking individuals. Correcting for censoring shows that women increasingly benefit from education all along the distribution of wages, even though part of this effect could be due to the effect of notional wages. The returns from schooling for husbands tell a different story. Husbands' schooling has an increasing positively impact on wages until highest quantiles, where the wider confidence bands show greater variability compared to lower quantiles: thus, very high levels of wage are explained by schooling only at a limited extent. Given the very small degree of censoring for husbands, the two graphs look almost identical.

All these econometric investigations show that the relationship between the variables of interest do not closely match the assumption of normality, since the estimates for the quantile regressors systematically depart from OLS estimates. This suggests that the phenomena under study involve significant substantial censoring and nonlinearities, two aspects that will be addressed in the empirical section of this article.

4.2 Estimation Technique

The estimation procedure is structured as follows:

1. The first problem to tackle when estimating the effects of sorting on observed labor behavior is obtaining reasonable estimates

of the expectations of e_i and s_i as they enter in the evaluation that prospective partners make while dating. We assume that prospective partners have rational expectations on each other's achievements, both in the educational system and in the job market. This implies that the observed values in the data for e_i and s_i can be used to recover their expected levels, provided that some sort of temporal smoothing is operated in order to obtain the expected values as computed before marriage. Since the data in SHIW have a panel structure, i.e. repeated observations across the years for the same couples, we can exploit this feature to obtain estimates of the variables relevant for the mating system. For computing expected education, we use the maximum level of schooling observed in the data. For computing expected salary, we use the median salary.

2. Since salary s_j is not observed for people unemployed or out of the labor force, we have left censoring for this variable:

$$s_j = \begin{cases} s_j^* & \text{if } s_j > 0 \\ 0 & \text{if } s_j \leq 0 \end{cases}$$

with $j \in \{w, h\}$. We use Heckman's model (Heckman, 1979) to account for censoring and estimate potential wages for nonworking wives and husbands. The regressors for wives' wages are schooling, expertise, expertise squared, professional qualification, and productive sector. The selection equation for wives includes age, age squared, schooling, schooling squared, number of children, dummies for geographical location, proxies for house ownership, non-labor income, and husband's wage. The squared term are inserted since the high degree of nonlinearities in wives' behavior. The equations for husbands parallel those for wives, except

for spouse's wage and professional qualification which are not included in the selection equation.

- Using predicted wages, we perform Three-Stage Least Squares procedure for the husbands' mating equations and another one for wives' mating equations. As a comparison, we also estimate a SUR model with all the four equations computed simultaneously. Along with direct and cross effects, mating equations contain controls for personal wealth (approximated by house ownership and income from capital), Inverse Mills' Ratio, job qualification, and number of children. Moreover, wife's wage mating equation also controls for notional wages.

5 Results

The results from the Heckman model for sample selection, obtained by Maximum Likelihood Estimation and displayed in tab. 3, highlight the concave effect of age on the probability of entering the job market. For women, the probability of being employed is maximized around 35 years. Merging this information with the significantly negative impact of children on labor market participation, it comes out that pregnancy and child rearing do impact the working position. The concavity of education on wives' wage is also confirmed by high estimated Student's t . Also, the same wage equation shows that expertise exerts a weak influence on wives' wage: while Becker (1991 [1981]) argues that the higher the husband's wage, the lower must result wives hazard for participation, Lam (1988) has proved that this holds true only when household production does not include public goods. The positive estimated coefficient in the present model supports the hypothesis that labor participation decisions of wives are mainly driven by public goods considerations.

Evidence from the mating equations, displayed in tables 6–5 show overall significance for both structural models, with R^2 s higher for educational mating. Checks for multicollinearity, not attached here but available upon demand, show tolerable values around 1.19 in the Variance Inflation Factor for all the four equations. To correct for spurious correlations induced by censoring, the Inverse Mills' Ratio and a dummy for censored observations were introduced and found significant for wives and for husbands.

All endogenous variables are estimated to be relevant in each equation, with some asymmetries across gender and the sharpest effects being the direct links between schooling levels and wage levels across partners. *The strong statistical and economic significance of cross-effects supports our hypothesis about the possibility of substitution between education and wages in the marriage market.* Wage impacts positively the educational mating equation, both for women and for men, as well as schooling impacts wage mating. The elasticity of an additional year of schooling, calculated around the mean, is 0.045 for women and 0.073 for men; moreover, the corresponding t values are found higher for men. Probably, since men are expected to provide the most part of family income, the effect of their wage is stronger when compared to women and allows men with higher wages to afford more educated wives. Contrasting these results with the crude estimates presented in tab. 2, it is a striking evidence that a structured model of marital sorting decreases observed schooling correlation from 64% to 42%. The issue of simultaneity is also relevant for the results: using as a benchmark a companion model of the same four equations obtained through SUR technique reported in tab. 7, assuming only links between error terms and not between variables, the 3SLS-estimated equations display non trivial differences between estimated coefficients. This also supports our initial conjecture that wages and education *jointly* impact the sorting between spouses and that simul-

taneity does matter.

Interestingly, the Inverse Mills' Ratio (λ), representing the hazard rate of nonparticipation, is also negatively related to prospective husband's and wives' expected education; in other words, *ceteris paribus*, women or men with higher probability of entering the job market are more likely than others to marry highly educated partners. Wages are sorted positively between partners, estimates say, and the effect is stronger from a prospective wife's standpoint, with a value of 30% for women and 16% for men. This is consistent with previous literature (Ermisch, 2003), since generally husbands transfer resources to their wives in exchange for household production. Accordingly, wives are expected to rely more on her husband's wage than the opposite. Minor findings show that better job positions impact positively on the probability of wage matching. Since the omitted category in the models is *worker*, results show that women are more responsive than men to job positions, because their estimated coefficients are uniformly higher than the corresponding figures for men.

It is instructive to compare our results with those obtained by Behrman, Birdsall, and Deolalikar (1995) and Brynin and Francesconi (2004). These authors estimate a mating equation of the type

$$e_w = d_1 e_b + \mathbf{x}_b^e \beta_b^e + \phi + \omega_w^e \quad (12)$$

where ϕ is an unobservable component of human capital to be estimated consistently from the post-regression residuals $\hat{e}_w - e_w$. They find that ϕ impacts positively on wages. Our results show that part of this unobservable variable depends upon wage, since marital sorting is multidimensional and education is not the only variable that prospective spouses may consider. If our interpretation holds true, then, the expected return of unobservable human capital to wages should be lower than Behrman's estimates. Lastly, an obvious way to extend

the present econometric exercise would be employing a technique of simultaneous quantile regressions, as indicated by Chernozhukov and Hansen (2006) and Kim and Muller (2004): although still in its infancy, this approach looks extremely promising for modeling complex and nonlinear links like those observed in the marriage market.

A Statistical Tables

A.1 Correlations

Table 1: Correlations – Censored Sample

Variables	Wife's Schooling	Husband's Schooling	Wife's Wage	Husband's Wage
Wife's Schooling	1.000			
Husband's Schooling	0.645	1.000		
Wife's Wage	0.382	0.306	1.000	
Husband's Wage	0.306	0.388	0.412	1.000

Table 2: Correlations – Uncensored Sample

Variables	Wife's Schooling	Husband's Schooling	Wife's Wage	Husband's Wage
Wife's Schooling	1.000			
Husband's Schooling	0.630	1.000		
Wife's Wage	0.225	0.178	1.000	
Husband's Wage	0.270	0.361	0.281	1.000

A.2 Heckman Equations

Table 3: Wives
HECKMAN SELECTION MODEL

VARIABLES	COEFFICIENTS		STATS	
	β	t	Mean	σ
Wife's Wage				
Wife's Schooling	0.141	7.368	2.264	0.511
Expertise	0.003	1.419	24.370	10.866
Expertise (Square)	0.981	2.113	0.071	0.056
Freelancer	0.058	1.090	0.005	0.072
Entrepreneur	-0.035	-1.056	0.014	0.118
Self-employed	-0.244	-12.804	0.080	0.272
Manufacturing	0.115	4.547	0.096	0.295
Marketing/Catering	0.105	3.958	0.086	0.281
Transportation/Communications	0.180	4.158	0.008	0.089
Finance	0.259	7.303	0.015	0.123
Public Administration/Service	0.240	9.538	0.238	0.426
Out of Labor Force	-0.103	-2.046	0.533	0.499
Constant	3.127	50.911		
Selection Equation				
Age	0.139	14.519	40.511	8.985
Age (Square)	-0.002	-14.492	1721.886	732.141
Wife's Schooling	-0.881	-13.390	2.264	0.511
Wife's Schooling (Square)	0.473	27.506	5.386	1.908
Number of Children	-0.150	-15.694	1.696	1.078
Husband's Wage	0.096	11.129	3.270	1.111
Freelancer	6.039	0.000	0.005	0.072
Entrepreneur	2.110	11.239	0.014	0.118
Self-employed	0.635	17.044	0.080	0.272
Constant	-3.571	-18.354		
$\tanh(\rho)$				
Constant	-0.901	-27.075		
$\ln(\sigma)$				
Constant	-0.680	-52.043		
Statistics				
Subjects	18,459			

Table 4: **Husbands**
HECKMAN SELECTION MODEL

VARIABLES	COEFFICIENTS		STATS	
	β	t	Mean	σ
Wife's Wage				
Husband's Schooling	0.291	31.386	2.303	0.476
Expertise	0.010	6.980	27.515	10.782
Expertise (Square)	-0.980	-3.706	0.087	0.062
Freelancer	0.458	23.848	0.028	0.165
Entrepreneur	0.170	11.395	0.048	0.214
Self-employed	-0.026	-2.828	0.208	0.406
Manufacturing	0.172	11.292	0.366	0.482
Marketing/Catering	0.117	6.936	0.144	0.351
Transportation/Communications	0.230	12.172	0.065	0.246
Finance	0.429	18.668	0.032	0.176
Public Administration/Service	0.277	17.421	0.299	0.458
Out of Labor Force	-0.010	-0.248	0.041	0.199
Constant	2.482	74.387		
Selection Equation				
Age	0.079	6.574	43.957	9.243
Age (Square)	-0.001	-7.311	2017.664	814.623
Husband's Schooling	0.337	12.517	2.303	0.476
Constant	-0.857	-3.312		
$\tanh(\rho)$				
Constant	0.222	2.911		
$\ln(\sigma)$				
Constant	-0.870	-126.090		
Statistics				
Subjects	18,459			

A.3 3SLS Estimation

Table 5: **Wives**
 DEPENDENT VARIABLES: *Log of schooling years, Log of wage*

VARIABLES	COEFFICIENTS		STATS	
	β	t	Mean	σ
Wife's Schooling				
Husband's Schooling	0.420	36.526	2.303	0.476
Husband's Wage	0.073	10.767	3.569	0.451
House Ownership	-0.004	-0.580	0.668	0.467
Husband's Inverse Mills' Ratio (λ)	-1.468	-19.014	0.174	0.068
Wife's Wage Censoring	-0.205	-34.590	0.571	0.495
Constant	1.411	34.780		
Wife's Wage				
Husband's Schooling	0.059	10.899	2.303	0.476
Husband's Wage	0.165	29.180	3.569	0.451
Income from Capital	0.003	4.665	6.970	3.387
Executive	0.038	3.951	0.062	0.242
Freelancer	0.069	4.822	0.028	0.166
Entrepreneur	0.034	3.089	0.048	0.214
Self-employed	-0.002	-0.277	0.208	0.406
Wife's Wage Censoring	0.037	7.641	0.571	0.495
Constant	2.709	129.763		
Statistics				
Subjects	18,086			
R^2 (Schooling)	0.444			
R^2 (Wage)	0.093			

Table 6: Husbands

DEPENDENT VARIABLES: *Log of schooling years, Log of wage*

VARIABLES	COEFFICIENTS		STATS	
	β	t	Mean	σ
Husband's Schooling				
Wife's Schooling	0.420	51.563	2.264	0.511
Wife's Wage	0.046	5.427	3.482	0.321
House Ownership	-0.046	-4.730	0.087	0.277
Wife's Inverse Mills' Ratio (λ)	-0.257	-25.955	0.977	0.419
Constant	1.445	37.254		
Husband's Wage				
Wife's Schooling	-0.065	-6.642	2.264	0.511
Wife's Wage	0.287	29.345	3.482	0.321
Number of Children	0.045	14.866	1.696	1.078
Income from Capital	-0.008	-7.545	0.989	2.706
Executive	0.038	1.578	0.016	0.124
Freelancer	-0.150	-3.564	0.005	0.072
Entrepreneur	-0.139	-5.183	0.014	0.118
Self-employed	-0.155	-13.298	0.080	0.272
Wife's Inverse Mills' Ratio (λ)	-0.456	-33.756	0.977	0.419
Constant	3.110	66.258		
Statistics				
Subjects	18,424			
R^2 (Schooling)	0.420			
R^2 (Wage)	0.182			

A.4 SUR Estimation

Table 7: SUR Estimation
 DEPENDENT VARIABLES: *Log of schooling years, Log of wage*

VARIABLES	COEFFICIENTS		STATS	
	β	t	Mean	σ
Wife's Schooling				
Husband's Schooling	0.797	83.397	2.303	0.475
Husband's Wage	0.062	11.084	3.569	0.451
House Ownership	-0.009	-1.752	0.669	0.466
Husband's Inverse Mills' Ratio (λ)	-0.793	-12.395	0.174	0.068
Wife's Wage Censoring	-0.098	-19.907	0.571	0.495
Constant	0.406	12.008		
Husband's Schooling				
Wife's Schooling	0.753	109.635	2.264	0.510
Wife's Wage	0.068	9.470	3.482	0.320
House Ownership	-0.025	-3.114	0.088	0.279
Wife's Inverse Mills' Ratio (λ)	-0.089	-10.629	0.977	0.420
Constant	0.450	13.830		
Wife's Wage				
Husband's Schooling	0.064	12.183	2.303	0.475
Husband's Wage	0.311	56.995	3.569	0.451
Income from Capital	0.002	3.464	6.982	3.377
Executive	0.030	3.192	0.062	0.242
Freelancer	0.059	4.221	0.028	0.165
Entrepreneur	0.026	2.495	0.048	0.214
Self-employed	0.001	0.235	0.208	0.406
Wife's Wage Censoring	0.059	12.778	0.571	0.495
Constant	2.167	106.857		
Husband's Wage				
Wife's Schooling	0.018	1.912	2.264	0.510
Wife's Wage	0.563	59.050	3.482	0.320
Number of Children	0.039	13.375	1.696	1.079
Income from Capital	-0.006	-5.883	1.007	2.727
Executive	0.038	1.615	0.016	0.124
Freelancer	-0.135	-3.291	0.005	0.072
Entrepreneur	-0.121	-4.604	0.014	0.118
Self-employed	-0.140	-12.212	0.080	0.272
Wife's Inverse Mills' Ratio (λ)	-0.368	-27.868	0.977	0.420
Constant	1.881	41.150		
Statistics				
Subjects	18,051			
R^2 (Husband's Schooling)	0.373			
R^2 (Husband's Wage)	0.348			
R^2 (Wife's Schooling)	0.051			
R^2 (Wife's Wage)	0.140			

B Graphs

B.1 Educational Mating

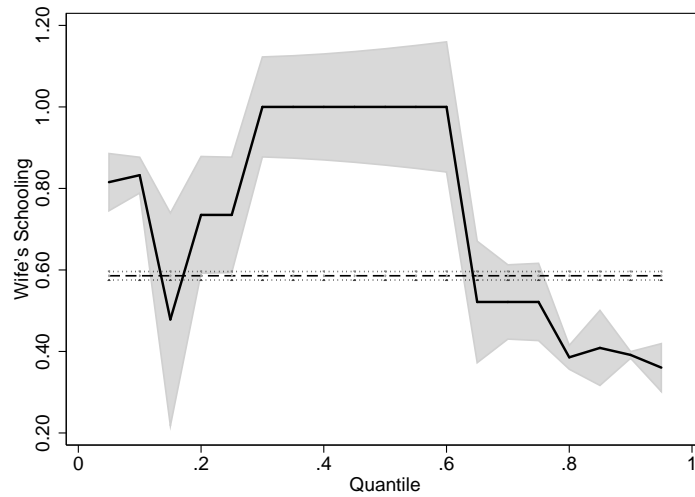


Figure 1: *Correlation between spouses' schooling (Uncensored sample).*

B.2 Wage Mating

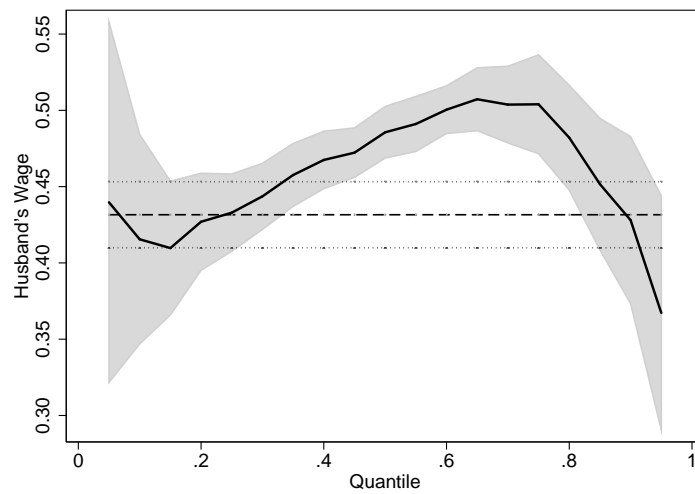


Figure 2: *Correlation between spouses' wages (Censored sample).*

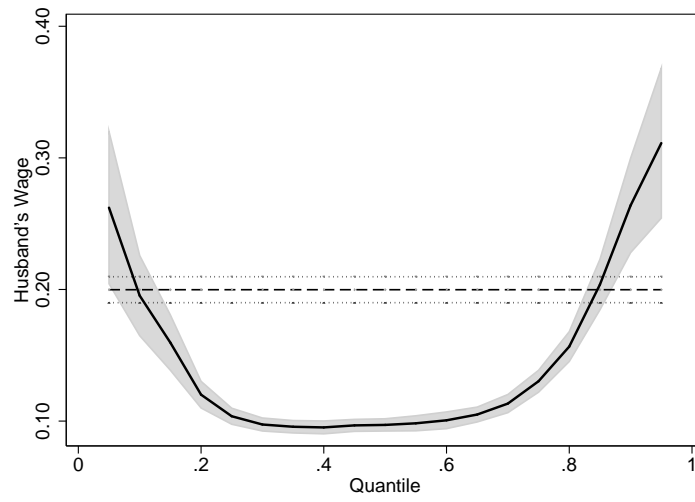


Figure 3: *Correlation between spouses' wages (Uncensored sample).*

B.3 Wives' Returns to Schooling

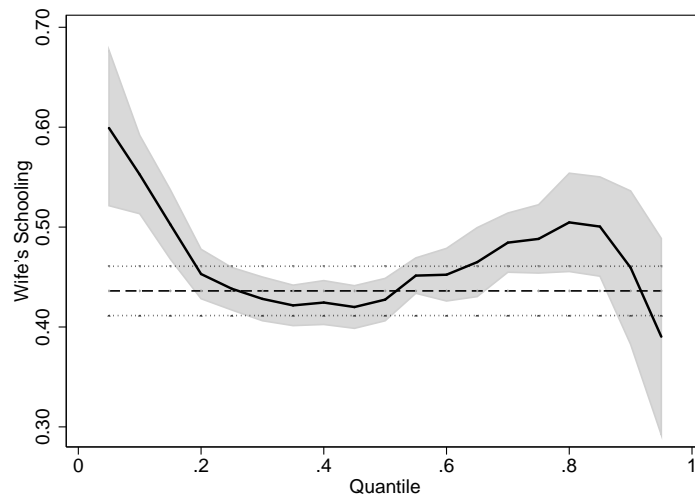


Figure 4: *The effect of wife's schooling on her wage (Censored sample).*

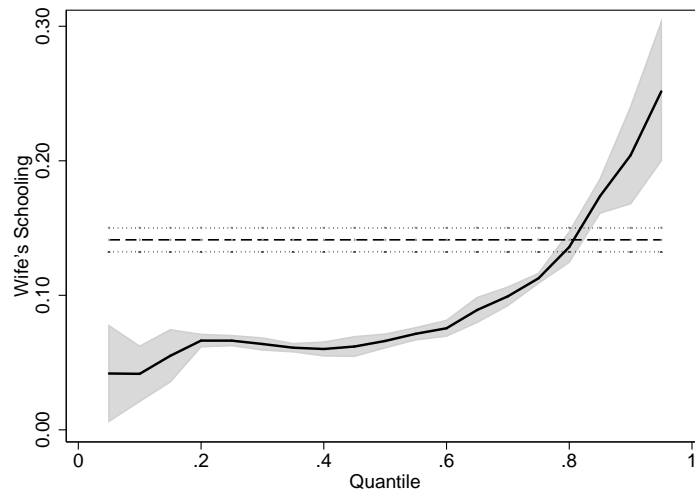


Figure 5: *The effect of wife's schooling on her wage (Uncensored sample).*

B.4 Husbands' Returns to Schooling

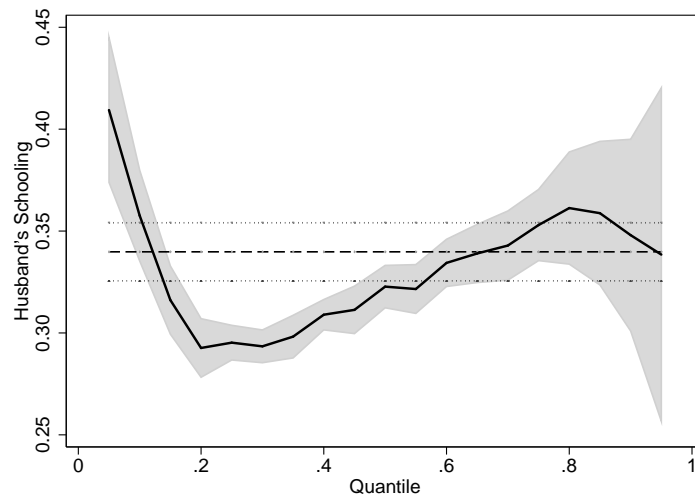


Figure 6: *The effect of husband's schooling on his wage (Censored sample).*

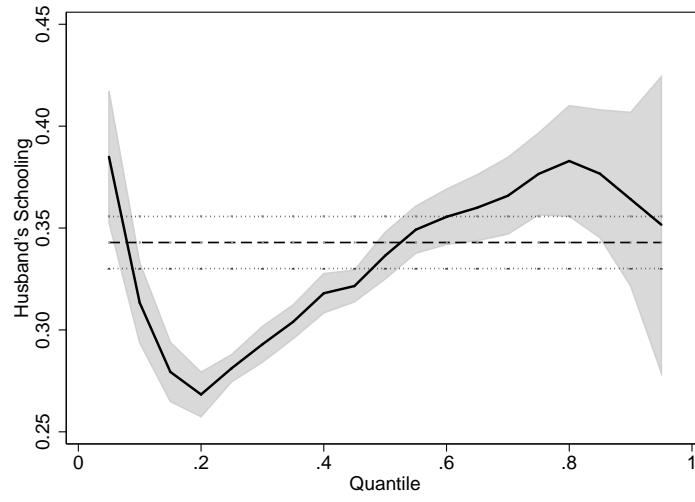


Figure 7: *The effect of husband's schooling on his wage (Uncensored sample).*

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