Male Marital Wage Premium across Generations in the US: A Revisit with Fixed Effect with Individual-Specific Slopes

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April, 2022

Abstract

Male marital wage premium (MWP) refers to the fact that married men earn more than unmarried ones. However, the effect of marriage on male's wage is still uncertain due to the potential selection bias. While past studies have controlled the wage selection bias, they did not control the potential wage growth until Ludwig and Brüderl (2018). In this paper, we utilize the fixed effect with individual-specific slopes (FEIS) developed by Ludwig and Brüderl (2018) to study MWP. We apply the FEIS to the US National Longitudinal Survey of Youth (NLSY) to study MWP in the NLSY79 and the NLSY97 generation. While we find positive and significant MWP with the treatment effect and the fixed effect model, we do not find significant MWP with the FEIS for both generations. In fact, the coefficients of the three models differ substantially, indicating potential biases with the two conventional approaches. Additionally, based on the FEIS estimates, the MWP seems to decrease in the later generation.

I. Introduction

"Male marital wage premium" (MWP), a well-known phenomenon, refers to the fact that married men earn more than unmarried ones. However, the effect of marriage on male wages is still uncertain partly due to the selection bias (i.e., males with high earnings are more sought-after in the marriage market) Past studies have examined the selection effect with either the treatment effect model or the fixed effect model, but their conclusions are conflicting. Some claim that MWP exists, while others argue otherwise.

While the selection effect has been a protracted debate (Nakosteen and Zimmer 1987; Korenman and Neumark 1991; Hersch and Stratton 2000), scholars mostly ignore the selection of high earning "potential." That is, males with high earning potential (not only pre-marriage wage level) can also be more likely to get married. Researchers do not control "potential wage growth" until Ludwig and Brüderl (2018). Ludwig and Brüderl (2018) develop the fixed effect with individual-specific slopes (FEIS), an adaptation of the conventional FE model. With this new method, researchers can consider individual's wage potential. Since the selection of earning potential is likely to exist, past findings of MWP could be problematic without using the FEIS. Thus, our paper aims to revisit the MWP with this new approach, compare the results with conventional methods (i.e., the treatment effect model and FE), and see if prior MWP findings are sensitive to different approaches.

This paper utilizes the US National Longitudinal Survey of Youth (NLSY) to study MWP across generations. The first generation comes from NLSY79, which surveyed people born between 1957 and 1964. We choose respondents from NLSY97 as our second generation in which the respondents were born between 1980 and 1984. Overall, we test the MWP of the two generations with the treatment effect, FE, and FEIS methods.

While we find positive and significant MWP with the treatment effect and the fixed effect model, we do not find significant MWP with the FEIS for both generations. In fact, the coefficients of the three models differ substantially, indicating potential biases with the two conventional approaches. Additionally, based on the FEIS estimates, the MWP seems to decrease in the later generation.

Overall, we demonstrate that MWP could be sensitive to how we control selection bias. Future scholars should be especially cautious when using the treatment effect model on cross-sectional data to study MWP. This warning is because our results with the treatment effect model is considerably higher than the two other methods.

The paper is organized as follows. Section II summarizes the past research on MWP and their methods for controlling the selection effect, and Section III specifies our approach and data. Section IV presents our results using the treatment effect model, FE and FEIS. Finally, we conclude our study in Section V.

II. Past Research on the Male Marital Wage Premium

The existence and the causal mechanism of male marital wage premium remain an active debate for social scientists. Scholars have proposed three main theories: market specialization[1], effort allocation[2], and employer bias[3], to explain the effect of marriage on male wage. The first claims that marriage allows husbands to invest more in market-specific skills, assuming the wives take care of the housework. The second mechanism, effort allocation, follows similar logic by saying that married men can devote more time to work. The last theory asserts that the employer could view married men as more productive. Or, the employers may consider married men as the breadwinners who deserve more financial support than unmarried ones.

Despite some empirical evidence of the three theories, potential selection into marriage may bias the results. That is, males with certain characteristics will be more likely to get married and earn more. For example, males with great personalities could be more successful in both marriage and job markets. Of course, males with high pre-marriage wage levels can also be popular in the marriage market. Overall, we might produce biased MWP estimates without considering potential selection issues.

Past attempts to rule out selection issues use either the treatment effect method (for cross-sectional data) or the fixed-effect method (for panel data)[4].

[1] Kenny (1983); Chun and Lee (2001)

[2] Becker (1985); Hersch and Stratton (2000); Stratton (2002)

[3] Siebert and Sloane (1981); Waite and Gallagher (2000); Grossbard-Shechtman and Neuman (2003)

[4] Nakosteen and Zimmer (1987); Ludwig and Brüderl (2018)

Treatment Effect

The treatment effect model controls selection endogeneity in a two-stage procedure proposed by Heckman (1978) and Barnow, Cain, and Goldberger (1980). With this approach, we can deal with selection issues with just the cross-sectional dataset. Nakosten and Zimmer (1987) are the first to utilize this technique and study MWP in the US. They conclude that there is no evidence of marital wage premium after considering selection bias.

Despite the consistent findings, we should not ignore the issue with the two-stage estimation method. Korenman and Neumark (1991) point out that the Inverse Mills Ratio in the second stage inevitably correlates with the explanatory variable by construction. The correlation creates multicollinearity, which then leads to a surge in the standard error[5]. In fact, the null finding in Nakosten and Zimmer (1987) can be explained by the increas of standard error alone since the coefficient did not change much with the selection control variable. The collinearity issue is most severe when the regressors for the two stages are the same (Bushway et al. 2007). Overall, we should be cautious when interpreting null results from the treatment effect model.

Fixed Effect and FEIS

Another approach is the FE model, which allows unobserved characteristics to be correlated with the regressors and controls for time-invariant omitted variables. Thus, employing the FE model should tackle the selection problem while avoiding the standard error issue of the treatment effect model.

Past researchers have adopted the FE model to study MWP. However, this method yields conflicting results.[6]. While some find significant MWP and claim a causal effect, some report that MWP disappears once individual time-invariant characteristics are controlled.

Despite the advantage of the conventional FE model, it requires strict exogeneity (i.e., the covariates from any period are uncorrelated with the error term from any period). In

[5]The uptick of standard error in the two-stage model is well known. Also see Moffitt (1999) and Stolzenberg and Relle (1990).

[6]See Korenman and Neumark 1991; Loh 1996; Comwell and Rupert 1997; Hersch and Stratton 2000; Ahituv and Lerman 2007; and Killewald and Gough 2013.

addition, it relies on the assumption of parallel trends between the "treated" and "untreated" groups (i.e., married and unmarried men). If the assumption is violated or the slopes are correlated with the parameter of interest, the coefficient estimate will be biased. Fortunately, the fixed effect with individual-specific slopes method (FEIS)[7], an adaptation of the FE model, could solve the problem. It requires a weaker form of exogeneity and allows heterogeneity in slopes (Ludwig and Brüderl 2018). Using the FEIS, Ludwig and Brüderl (2018) demonstrate no causal effect of MWP if the slope of wage trajectory is controlled. That is, the expected wage growth is also a source of selection bias.

Although FEIS seems to be the most flexible model presented here, it requires relatively complete data, which may limit its usage. To be more specific, the number of periods (denoted as T) needs to be bigger than the number of covariates (denoted as J) selected to have individual-specific slopes. For example, if we choose work experience and its square as the variables with individual-specific slopes (J = 2) (i.e., $\alpha_i exp_{it}$ and $\alpha_i exp_{it}^2$), all individuals with less than three periods of information will be dropped. This requirement could render many data invalid, resulting in a larger standard error.

III. Research Design

Identification Strategy

To re-examine MWP in the US, we first employ the treatment effect model and the conventional fixed effect model as the benchmark. Then, we introduce the FEIS to see if the results change substantially.

The treatment effect model follows Heckman's (1979) and Nakosteen and Zimmer (1987) proposed method to tackle selection bias. We first consider the marriage equation (Equation 1) and wage equations (Equation 2) separately (i.e., treat marriage as an endogenous variable). Afterward, we estimate the combination of the two models and calculate the Inverse Mills Ratio for every individual. Finally, we put the Inverse Mills Ratio as a right-hand-side variable along with marital status and other controls in the wage equation. Equation 3 illustrates the model for estimation:

[7] $\ln w_{it} = \alpha_{2i} exp_{it} + \beta m_{it} + X_{it}\gamma + \alpha_{1i} + \epsilon_{it}$.

$$m_i^* = c + \lambda \ln w_i + \theta Y_i + u_i. \quad (1)$$

$$\ln w_i = \alpha + \beta m_i + \gamma X_i + \epsilon_i. \quad (2)$$

$$\ln w_i = \alpha + \beta m_i + \eta MR_i + +\gamma X_i + \epsilon_i. \quad (3)$$

, where m_i^* is the dummy for marital status, MR is the Mills Ratio, and Y_i and X_i are the control variables.

For the fixed effect model, our estimation is implemented at the individual-year level since we have annual observations of individual wages. Equation 4 describes the model:

$$\ln w_{it} = \alpha_2 exp_{it} + \beta m_{it} + X_{it}\gamma + \alpha_{1i} + \epsilon_{it}. \quad (4)$$

Where lnw_{it} denotes the outcome of interest: the natural log of person i's wage at time t. exp_{it} is labor market experience, and X_{it} are the control variables. The key variable used for identification in our regression is the marriage dummy, m_{it} such that m_{it}= 1 for a married person. The wage level α_{1i} is an individual-specific constant, as well as α_{2i}.

$$\ln w_{it} = \alpha_{2i} exp_{it} + \beta m_{it} + X_{it}\gamma + \alpha_{1i} + \epsilon_{it}. \quad (5)$$

Data

To evaluate MWP across time, we gather data from the US National Longitudinal Survey of Youth. The first generation we examine is from the NLSY79, born between 1957 and 1964. The cohort was first surveyed in 1979 when they were 14 to 22 years old. This panel data tracks men throughout their adulthood, which allows us to identify the MWP with FE and FEIS approaches. For the treatment effect model, we select responses in 1998 as our cross-sectional data. The cohort was between 34 and 41 at that time, so we capture the period when these people were in their first marriage and a stable job.

We choose NLSY97 as our second generation of interest. The NLSY97 surveyed men and women born between 1980 and 1984. We select responses in 2017 as our cross-sectional data, and the cohort was between 33 and 37 at that time.

Wage: To be consistent with previous literature, we use the (natural) log of the hourly wage of the respondent's primary job. We also rule out outliers by setting wages lower than 50 cents or higher than 500 dollars to missing.

Marital Status: Following previous research, we investigate the effect of the first marriage only. We thus use a dummy variable, "marry," indicating whether the respondents were in their first marriage at the time of the interview.

Control Variables: We employ similar but not the same control variables in FE/FEIS and the treatment effect model. For FE and FEIS, we include dummies for the number of children, job tenure, years of education, a dummy for living in the urban area, work experience, and the square of work experience. It should be noted that the work experience and its square are used to capture individual wage growth in the FEIS model ($\alpha_2 exp_{it}$). Overall, the list is similar to past studies using the FE and FEIS models.

Regarding the treatment effect model, we need variables to predict marriage in the first stage and another set of variables for the second stage. To predict marriage, we use a dummy for non-black and non-Hispanic, a dummy for living in the urban area, age, work experience and its square, current enrollment in a school, and years of education. In the second stage, we add job tenure and the dummies for number of children to the list of variables in the first stage, and take out age and enrollment. In Appendix, we also include individuals' height, the square of height, BMI, and the square of BMI in the first stage to check if the collinearity issue arises (Table 3 in Appendix).

Sample Selection

Before our analysis, we carefully select our data by the following criteria. First, we exclude id-year that were self-employed at the time. This move is consistent with previous literature claiming self-employed people's earnings are a problematic measure of their labor income (Fairlie 2005; Killewald and Gough 2013; Ludwig and Brüderl 2018). Next, we rule out the person-years with invalid marital status and people who married before participating in the survey. Because we focus on the effect of the "first marriage" only, we exclude person-years that got separated, divorced, and widowed. We further rule out person-years that were married for more than 15 years. To deal with wage coding errors and outliers, we restrict our samples to those who earn more than 0.5 dollars and less than 500 per hour. Finally, we only keep men with more or equal to four years of observations in our data.

Since the cross-sectional data for the treatment effect model have fewer observations, we reduce our sample restrictions to keep more data. We just include males with hourly wages between 0.5 and 500 dollars and self-employed males. In Table 4 in Appendix, we also use the full restriction as our panel data to compare with the fixed effect and the FEIS models, and the results are similar to our main findings.

IV. Results

This section presents the empirical results of the two generations: NLSY79 and NLSY97. *Generation NLSY 79*: Table 1 shows the results using the treatment effect, FE, and FEIS. The treatment effect model suggests that married men, on average, earn 67 percent more than unmarried men after adjusting for selection bias. The coefficient is considerably large and significant. Nevertheless, the standard error of the marriage coefficient in the treatment model is the largest with 0.085, which reinforces the idea that the treatment effect model may produce imprecise MWP estimates (Korenman and Neumark 1991) [8].

For the FE and FEIS models, they reveal a 5.4 percent and 0.7 percent wage premium for married men, respectively. However, the result in the FEIS model is not statistically significant. To interpret the reason behind the null result, we could compare the estimates of FE and FEIS since the models are almost identical except for the slopes in FEIS. Figure 1 demonstrates the substantial shrinkage of the marry coefficient in the FEIS model. The stark contrast between the two models indicates that the null results should be driven by controlling potential wage growth rather than the standard error rise. Finally, since the coefficients change considerably with FEIS, past research using treatment effect and FE to study MWP could be biased.

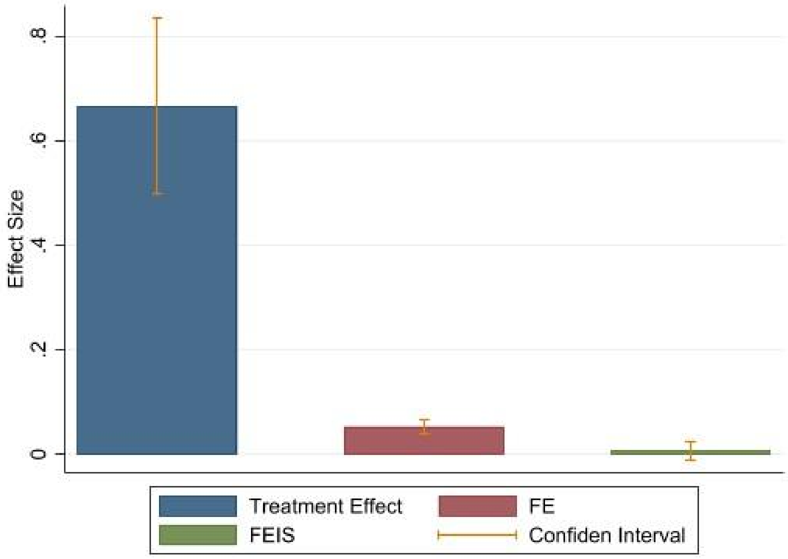
[8] Admittedly, the fact that the treatment effect model uses fewer observations could result in larger standard error.

Table 1 Regression using NLSY1979 data

Variable	**Treatment 1998 Basic**	**FE**	**FEIS**
marry	0.666***	0.054***	0.007
	(0.0854)	(0.007)	(0.009)
urban	0.061**	0.025***	0.016***
	(0.021)	(0.003)	(0.004)
exp	0.025	0.052***	
	(0.009)	(0.001)	
expsq	-0.029	-0.105***	
	(0.051)	(0.005)	
$lnIMR$	-0.595***		
	(0.046)		
Standard Controls			
tenure	0.015***	0.011***	0.005**
	(0.002)	(0.001)	(0.002)
eduyear	0.073***	0.090***	0.034***
	(0.005)	(0.002)	(0.006)
Sample Size	3125	40644	40605
R^2		0.36	
Year FE	Y	Y	Y

Note: Standard controls also include the dummies for number of children and the dummy for race. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Figure 1: MWP of Three Models Using NLSY79



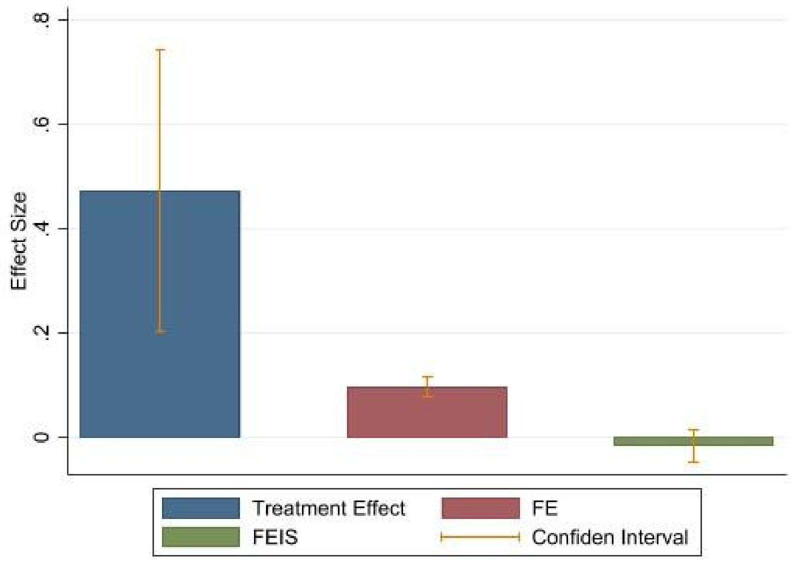
Generation NLSY97: Now we investigate the MWP of the new generation. Table 2 demonstrates the regression results using the treatment effect, FE, and FEIS. First, the treatment effect model indicates that married men earn 47 percent more wage than unmarried ones, controlling for selection bias. In contrast, the FE and FEIS reveal a 9.7 percent wage increase and 1.7 percent wage "decrease" for married men, respectively. That said, the result with FEIS is not significant. Overall, a similar pattern appears when we compare the results from the two generations. The treatment effect model produces the largest point estimates but also the biggest standard errors, and the FEIS shows small and insignificant results. By comparing the FE and FEIS in Figure 2, we also see that the null result in FEIS is mainly due to the decrease in the point estimate instead of the increase in the standard error.

Table 2 Regression using NLSY1997 data

Variable	Treatment 2017 Basic	FE	FEIS
marry	0.473***	0.097***	-0.017
	(0.138)	(0.010)	(0.016)
urban	0.108***	0.019*	0.017
	(0.028)	(0.009)	(0.013)
exp	0.055***	0.046***	
	(0.013)	(0.002)	
expsq	-0.158**	-0.064**	
	(0.050)	(0.010)	
lnIMR	-0.656***		
	(0.044)		
Standard Controls			
tenure	0.010***	0.008**	0.003
	(0.002)	(0.001)	(0.003)
eduyear	0.063***	0.072***	0.003
	(0.005)	(0.002)	(0.006)
Sample Size	2425	24370	24222
R^2		0.318	
Year FE	Y	Y	Y

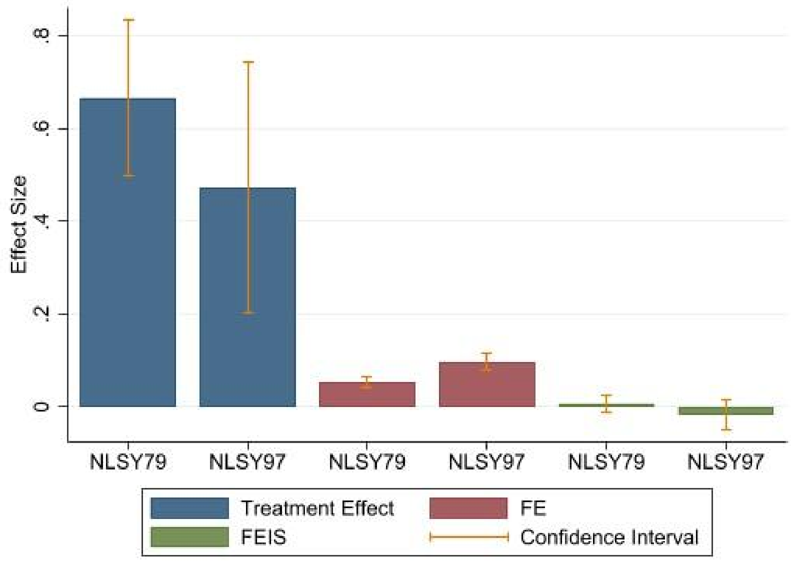
Note: Standard controls also include the dummies for number of children and the dummy for race. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Figure 2: MWP of Three Models Using NLSY97



Our final goal is to compare the MWP across the two generations. The treatment effect model reveals a decrease in MWP from 67% in NLSY79 to 47% in NLSY97. Contrastingly, the fixed effect model predicts an higher MWP in the later generation. Of course, the discrepancy in the results of the two conventional methods may just reinforce the idea that they produce biased estimates. Consequently, we should focus on the results using FEIS. As discussed before, the MWP is 0.7 percent for NLSY79 and -1.6 percent for NLSY97. The change in the point estimates and confidence interval (see Figure 3) indicates a decrease in MWP for the new generation, as predicted. However, it should be noted that the two estimates are both statistically insignificant from zero.

Figure 3: Confidence Interval of Three Models



V. Conclusion

While the debate over male wage premium and the selection bias is well known, past studies did not control the selection of potential wage growth until Ludwig and Brüderl (2018). The neglection is problematic since males with high earning potential should also be popular in the marriage market. This paper examines three different methods to control selection bias: treatment effect model, fixed effect model, and fixed effect with individual-specific slopes (FEIS). The first two methods are conventional, whereas the last one is relatively new in the literature. We argue that the FEIS model is a more appropriate approach to the selection problem in MWP since it controls individuals' potential wage growth. Thus, previous studies without controlling such a factor can be biased. To examine the potential bias of the treatment effect and fixed effect model, we investigate the MWP in two generations of the US (i.e., NLSY79 and NLSY97) using the two conventional methods plus the new FEIS approach. Aside from comparing results from three different models, we also predict that the MWP should decrease in the later generation where the gender norm is less dogmatic, especially when we use the FEIS.

We find significant MWP with treatment effect and fixed effect models for the NLSY79 and NLSY97 generation, whereas we do not find significant MWP with FEIS across the two generations. The point estimates vary with model selection, indicating potential biases in the conventional methods. Also, the MWP seems to decrease in the later generation, which is consistent with our prediction.

Admittedly, comparing the treatment effect model and the other two models may still be problematic empirically and theoretically. First, the MWP estimates of our treatment effect model are really sensitive to the selected year [9], and we cannot explain this inconsistency. Theoretically, we do not prove why the FE or FEIS may produce very different estimates than the treatment effect model. This shortcoming means that the advantage of FEIS over the treatment effect model is less conclusive.

Despite the weaknesses, we contribute to the field by showcasing the stark difference in the results produced by treatment effect, FE, and FEIS model. Thus, future scholars should be cautious when choosing their methods to rule out selection effects. We warn against using cross-sectional data to study MWP since the treatment effect model produces considerably larger MWP estimates than FE and FEIS. By comparing MWP across generations, we also show that MWP could change with time, implying the effect of shifting social norms in the US.

Finally, future scholars could investigate when the selection effect is strong and when it is not. Since the selection bias (both wage level and potential wage growth) implies that some people seek high earning or high earning potential males as husbands, it is interesting to see if the selection effect fades when the social perception of an "ideal husband" changes.

[9] Recall that we use one year of the panel data as our cross-sectional data.

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Appendix

Table 3 Regression using NLSY1979 data

Variable	**Treatment 1998 Appearance**	**Treatment 1998 Basic Restricted**
marry	0.686***	0.690***
	(0.051)	(0.099)
urban	0.045**	0.073*
	(0.017)	(0.033)
exp	0.035*	0.064*
	(0.028)	(0.029)
expsq	-0.058	-0.169
	(0.055)	(0.095)
$lnIMR$	-0.602***	-0.703***
	(0.026)	(0.045)
Standard Controls		
tenure	0.015***	0.014***
	(0.002)	(0.003)
eduyear	0.072***	0.091***
	(0.005)	(0.006)
Sample Size	2661	1261
Year FE	Y	Y

Note: Standard controls also include the dummies for number of children and the dummy for race. In Treatment 1998 Appearance, we consider individual's height, the square of height, BMI, and the square of BMI in the first stage to check if the colinearity issue arises. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.

Table 4 Regression using NLSY1997 data

Variable	Treatment 2017 Appearance	Treatment 2017 Basic Restricted
marry	0.455**	0.652***
	(0.143)	(0.171)
urban	0.121***	0.108**
	(0.028)	(0.039)
exp	0.052***	0.041*
	(0.013)	(0.019)
expsq	-0.148**	-0.096
	(0.052)	(0.068)
lnIMR	-0.657***	-0.628***
	(0.043)	(0.081)
Standard Controls		
tenure	0.009***	0.006
	(0.002)	(0.003)
eduyear	0.064***	0.055***
	(0.006)	(0.008)
Sample Size	2258	1184
Year FE	Y	Y

Note: Standard controls also include the dummies for number of children and the dummy for race. In Treatment 2017 Appearance, we consider individual's height, the square of height, BMI, and the square of BMI in the first stage to check if the colinearity issue arises. * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$.