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[1]We thank Kegon Tan for a fruitful discussion at the start of this project.

Abstract

In the US labor market, married men and women earn higher wages than their single counterparts. At the same time, individuals with higher cognitive and non-cognitive skills are more likely to be married. We extend the frameworks of Altonji and Pierret (2001) and Pinkston (2009) to the case of marriage and find no evidence that employers use marriage to statistically discriminate workers. Contrary to what statistical discrimination implies, the returns to being married increase with labor market experience. For women without experience being married is associated with a penalty. However, as experience increases, the relationship between wages and being married becomes positive. These findings are valuable in building a better understanding of the determinants of the marriage wage premium.

Keywords

Marriage Wage Premium, Employer Learning, Statistical Discrimination.

JEL Classification

J12, J16, J30.

1 Introduction

In the US labor market, married individuals earn higher hourly wages than their single counterparts, the so-called marriage wage premium (MWP). The men's premium has been long established, while for women, the relationship between being married and wages has evolved from a penalty to a premium over the last decades (McConnell and Valladares-Esteban, 2023). In the literature that studies the men's MWP, some authors, starting with Hill (1979) and Bartlett and Callahan (1984), hypothesize that the premium could result from positive employer statistical discrimination.[1] The idea is that marriage might be positively related to variables relevant to productivity which are hard to observe by employers, while marital status is much easier to observe.[2]

We use two key frameworks in the literature on employer learning and statistical discrimination to investigate the discrimination hypothesis. First, we adapt the public learning setup of Altonji and Pierret (2001) for education and race to the case of marriage. The main idea is that as workers' experience in the labor market increases, the returns on easy-to-observe variables vis-à-vis the returns on hard-to-observe variables are informative of the existence of employer learning and statistical discrimination. We also consider the asymmetric learning (or private learning) framework of Schönberg (2007) and Pinkston (2009), which are an extension of the setup of Altonji and Pierret (2001). The asymmetric information setting allows for a distinction between the learning done by the current employer, which occurs over the tenure of a job, and the public learning that happens through the overall experience of a worker in the labor market.

We start our analysis by documenting that for both men and women, cognitive and non-cognitive skills, measured before individuals enter the labor market, are correlated with being married later in life. Thus, we document the basis for potential statistical discrimination on marital status.

Then, we assess the discrimination hypothesis using a public learning framework like the one by Altonji and Pierret (2001). The main mechanism can be described as follows. Employers value the productivity of workers. Some of the determinants of productivity are easily observable by employers, while others are not. Without loss of generality, consider one easy-to-observe variable, such as marital status (which might or might not affect productivity), and a hard-to-observe variable, such as cognitive ability/intelligence which determines productivity. Altonji and Pierret (2001) show that if these two variables are positively correlated, their returns in a wage equation indicate if there is employer learning and statistical discrimination. First, if the returns to the hard-to-observe variable increase with experience, that indicates employer learning. The rationale is that, as the worker accumulates experience in the labor market, employers can better discern workers' true endowment of the hard-to-observe variable. Second, in the presence of statistical discrimination, i.e., when the easy-to-observe variable is used to proxy the hard-to-observe variable, the returns on the easy-to-observe variable decrease with experience. That is, the easy-to-observe variable's informational content decreases, and its return diminishes.

The patterns we find in the data are consistent with employer learning but not statistical discrimination. In fact, for both men and women, the interaction between being married and experience is positive, the opposite of what discrimination would imply. For men, we find that married men with no experience earn higher wages than their single counterparts, and the difference increases with experience. However, women with no experience earn lower wages than their single counterparts. The women's premium only emerges as experience increases. We show that the returns of being married and experience are similar

[1] In Appendix Section A, we discuss the different forms discrimination might take to generate a higher wage for married individuals and conclude that statistical discrimination is the only channel that merits empirical consideration.

[2] In the US, it is illegal to discriminate based on marital status. Moreover, it is also illegal to ask job seekers and employees to disclose their marital status. However, the implicit assumption is that it is easy for employers to have an accurate approximation of the marital status of a job applicant/worker. Consider the content of casual conversations in the workplace, the fact that many individuals display their marital status through elements of clothing (such as wedding rings), or that if there exists positive discrimination towards married individuals, it is beneficial for these individuals to reveal this information to their (potential) employer voluntarily.

for men with and without college degrees.[3] In contrast, women's patterns are mainly driven by those without a college education. We reach similar conclusions when we consider the case of private employer learning.

We make two contributions. First, we contribute to the literature on the relationship between marriage and wages. Although several authors in this literature (Korenman and Neumark, 1991; Ginther and Zavodny, 2001; Antonovics and Town, 2004) mention the possibility that statistical discrimination might explain the men's marriage wage premium, there has been no formal test of this hypothesis.[4] We provide a formal test for the discrimination hypothesis by extending the frameworks of Altonji and Pierret (2001) and Schönberg (2007) – Pinkston (2009) to the case of marriage.

Second, we contribute to the employer learning and statistical discrimination literature by expanding the worker attributes employers may use to infer hard-to-observe ability measures. The choice of marital status as a potential discriminant, while often suggested in the MWP literature, is novel in the employer learning and statistical discrimination literature, as is the joint consideration of cognitive and non-cognitive skill measures.

2 Data and Descriptive Evidence

2.1 Data

In order to test implications of the EL-SD models we consider, we base our analysis on the NLSY79. Given the differences in marital patterns across racial groups, we focus specifically on the white cross-sectional sub-samples for men and women. We restrict the age range of our sample members to 22-45 in order to i.) focus on the earlier period of the employment life-cycle, as this is when employer learning should be more prevalent and ii.) obviate the consequences of attrition as panel members age.

We select the sample restrictions to balance two objectives. First, we follow the EL-SD literature as much as possible so that our results are comparable to those in the literature. Secondly, we restrict the sample to account for the fact that marital status can change over time. Hence, we restrict our sample to job-spells where individuals' marital status does not change.

Broadly speaking, we follow the criteria laid out in Altonji and Pierret (2001), Pinkston (2009), and Arcidiacono, Bayer, and Hizmo (2010). Because we do not focus on education as the easy-to-observe variable, we do not impose further restrictions based on educational attainment. As in Pinkston (2009), we drop observations where the measure of actual experience exceeds potential experience by a year or more. For ever-married individuals, we consider marital status in each of their job-spells, and restrict the sample to job-spells where the ever-married enter the job married. If individuals become divorced, we remove subsequent job-spells. As our focus is on employer learning and statistical discrimination based on marital status, job spells that occur before marriage for those who marry by the last time we see them are not informative of the mechanism we test. We also aim to rule out cases where there is employee learning about the statistical discrimination process, if it exists, whereby individuals make marital decisions based on perceived employer-based statistical discrimination.

[3]In exploring heterogeneity by educational attainment, we corroborate a key finding of Arcidiacono, Bayer, and Hizmo (2010): Employers learn about the cognitive ability of men without a college degree as they accrue experience, but for those with a college degree, wages are set as if employers observe cognitive ability. Arcidiacono et al. (2010) propose that for recent college graduates, their resumes will convey much of the information required (test score, degree major, college attended) to form a sense of their cognitive ability. We show that the same patterns extend to women.

[4]Maasoumi, Millimet, and Sarkar (2009) use the Panel Study of Income Dynamics (PSID) to estimate the men's MWP along the wage distribution. Because they find a premium only at the lower end of the wage distribution, they conclude that discrimination is likely the cause of the premium. de Linde Leonard and Stanley (2015) run a meta-analysis of the literature on men's MWP and conjecture that discrimination might be the source of the premium as the meta-analysis indicates that the MWP increases with years of marriage. However, these studies do not formally test the employer discrimination hypothesis.

In our empirical strategy, presented below in Section 3.1, we consider two hard-to-observe determinants of productivity. First, cognitive ability, which we proxy with the Armed Forces Qualification Test score (AFQT). As is common in the EL-SD literature, we use the normalized and age-adjusted Armed Forces Qualification Test score (AFQT) from the NLSY as a measure of cognitive ability. Secondly we construct an index of non-cognitive ability. For this non-cognitive measure, we estimate a single factor index via Maximum Likelihood, based on 10 self-esteem questions (the individual questions from the Rosenberg Self-Esteem Scale, questions administered in 1980) and the Rotter Locus of Control Scale (administered in 1979). We present the factor loadings for the non-cognitive index in Table A1. Given that the inputs into our non-cognitive index are administered in 1979 and 1980, a sample requirement is for the sample member to respond to the NLSY in both years.

Table A2 presents the summary statistics of the sample we use to test the to EL-SD models we consider.

2.2 Marriage, AFQT and Non-Cognitive Measures

We start by exploring the extent to which cognitive scores and non-cognitive scores are correlated with later marital status and present the resulting estimates in Table 1. We normalize both scores based on the regression sample, so the coefficient can be interpreted as the impact of a 1 standard deviation increase in the respective score. Columns 1 and 2 respectively show that men with higher non-cognitive score and cognitive scores are more likely to get married (and stay married) in the future. Interesting, when we condition on both scores simultaneously, it is only the non-cognitive index that has a statistically significant conditional correlation with future marital status. Thus, for men, measures of self-esteem and self-perceived agency in late teens or early adulthood are predictive of getting and staying married for men.

For women, the results in columns 4 and 5 highlight a similar pattern to men – women with higher non-cognitive and cognitive scores are also more likely to marry. The coefficient on AFQT is twice as large as that on the non-cognitive index however. When we simultaneously enter both measures into the regression, we find no significant impact of non-cognitives on later marital status, but a statistically significant impact of cognitive ability.

The evidence we provide in this section highlights the link between hard-to-observe determinants of productivity (non-cognitive measures and ability proxies) and later marital status. Although there is limited work exploring this topic, our results are broadly consistent with empirical findings documented by other scholars. Lundberg (2012) studies the marital consequences of the personality traits, specifically the Big Five personality traits. With some exceptions, Lundberg (2012) typically finds consistent patterns of the impact of personality traits on getting married, and staying married, across the genders. Aspara et al. (2018) document a positive relationship between cognitive measures and later marriage for a large sample of Finnish men. The authors interpret their findings through the lens of evolutionary theory, considering intelligence measures as tacit "fitness indicators" in the marriage market.

For both genders the relationship between the two scores and marital status is positive. This suggests that, to the extent employers have some awareness of this positive relationship, marital status could be used a variable on which employers statistically discriminate.

3 Symmetric Learning

In this section, we consider a model of public or symmetric learning, whereby all firms in the market learn the agents type in the same manner. Later on, we extend this model to allow for asymmetric learning, where a worker's current employer has an informational advantage over the rest of the labor market in learning the agent's type. Whilst the asymmetric model feels intuitively more apt, we do not find a single instance in any regression specification of private learning playing a core role in wage determination

Table 1: Non-Cognitive Index, AFQT and Later Marital Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Men			**Women**		
	Non-Cognitive Index Only	Cognitive Measure Only	Both Measures	Non-Cognitive Index Only	Cognitive Measure Only	Both Measures
Non-Cognitive Index	0.039***		0.037***	0.020*		0.015
	(0.010)		(0.011)	(0.011)		(0.011)
AFQT Score		0.027**	0.020		0.040***	0.037***
		(0.013)	(0.013)		(0.014)	(0.014)
Observations	16,562	16,562	16,562	13,997	13,997	13,997
$\overline{Y}$	0.557	0.557	0.557	0.628	0.628	0.628

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. Parameters estimated via logit. Average marginal effects are presented above. The following controls are included: dummies for highest level of educational attainment, a dummy for urban residence, region in 1979 dummies, cohort dummies, year dummies, maternal education, paternal education, dummies based on the following measures when respondent was 14: father worked, mother worked, father absent, mother absent, household received newspapers, household had a library card. Non-cognitive index is a single factor based on 10 self-esteem questions (Rosenberg Self-Esteem Scale, questions administered in 1980) and the Rotter Locus of Control Scale (administered in 1979). Both the non-cognitive index and the AFQT measure are standardized. Data used: NLSY79, 1981-2012.

for either men or for women. Hence, we focus our attention on the symmetric learning model in the main body of this work, and present the asymmetric learning model, along with accompanying empirical results, in Appendix C.

3.1 Empirical Specification

We consider the following specification:

$$y_i = \alpha_0 M_i + \alpha_1(M_i \times x_i) + \beta_0 A_i + \beta_1(A_i \times x_i) + \delta_0 NC_i + \delta_1(NC_i \times x_i) + C_i^{'}\gamma + \epsilon_i. \quad (1)$$

y_i is the natural log of wages in 2006 Dollars. M_i is an indicator for being married. A_i and NC_i are the two hard-to-observe determinants of productivity, respectively cognitive and non-cognitive abilities. As is common in the EL-SD literature, we use the normalized and age-adjusted Armed Forces Qualification Test score (AFQT) from the NLSY as a measure of cognitive ability/intelligence. For the non-cognitive measure, we estimate a single factor index via Maximum Likelihood, based on 10 self-esteem questions (the individual questions from the Rosenberg Self-Esteem Scale, questions administered in 1980) and the Rotter Locus of Control Scale (administered in 1979). $(M_i \times x_i)$, $(A_i \times x_i)$, and $(NC_i \times x_i)$ are interactions between labor market experience (x_i) and, respectively, marriage (M_i), AFQT (A_i), and the non-cognitive index (NC_i). The vector C_i contains a series of control variables. We follow the literature to include: highest educational attainment dummies, interactions of educational attainment dummies with time (to absorb changing returns to education), year dummies, polynomials up to order three experience (to not conflate changes that occur over time with the experience interaction of focus), an urban residence indicator, children dummies, and tenure.

A common issue in this framework is the fact that cognitive ability might determine actual experience and bias the estimates which are interacted with this variable. We follow the common approach in the literature and instrument experience with potential experience.[5]

3.2 Results

Table 2 and Table 3 present the results for men and women, respectively. We report the coefficients from four different specifications, incrementally adding regressors, to show the impact of their inclusion on the

[5]In the IV regression all instances of actual experience (polynomials and interaction terms) are instrumented.

estimated coefficients associated with marriage, the easy-to-observe variable, and AFQT and the non-cognitive index as the hard-to-observe variables. In both tables, columns (1) to (4) display the estimated coefficients when we use potential experience as x_i in Equation 1. In columns (5) to (8) we report the estimates for the case in which we use actual experience instrumented with potential experience as x_i.

The theory predicts that if employer learning is present, the returns to the hard-to-observe variables will increase with experience. That is, the interaction between experience and respectively AFQT and the non-cognitive index should both be positive. Positive employer discrimination implies that the returns to the easy-to-observe variable are positive when the worker has no experience and decrease while the worker accumulates experience. Hence, the married coefficient should be positive while the interaction between marriage and experience should be negative. We do not find this to be the case for either men or for women.

We start with men, presenting our core estimates in Table 2, and note that the patterns of the OLS and IV estimates are almost identical. For this reason, we will direct our primary attention to the IV results. In columns (1) and (5), when we regress wages only on marriage and control variables, we document a significant conditional correlation between being married and wages. This estimate is empirically consistent with the OLS-esimated marriage wage premium we document in a companion paper (McConnell and Valladares-Esteban, 2023). When we include our two ability scores in to the regression specification in columns (2) and (6), we find the conditional correlation between marriage and wages to be stable. In addition, we document the importance of both of these ability measures in determining wages, with the role of cognitive ability roughly twice as large as that of the non-cognitive measure we use in this work.

In his work, Pinkston (2009) reiterates an insight from Altonji and Pierret (2001) – if we run a regression with an experience interaction for the easy-to-observe variable, without the concomittant interaction for the hard-to-observe variables, employer learning predicts that the coefficient on the interaction term should be zero. The intuition behind this is that we should *only* expect to see a decline in the importance of the easy-to-observe variable when we allow employers to learn about the hard-to-observe variables. In this sense, columns (3) and (7) provide the first evidence for employer learning in our context, even though these are not the correctly specified regression models.

The inclusion of the interaction between marriage and experience in the regression, columns (3) and (7), reveals that the marriage premium of men increases over the working life. As we note above, without the experience interactions with the two hard-to-observe variables, this is not an indication of employer learning, but rather some other mechanism.[6] According to the IV estimates in column (7), the marriage premium of men with no experience is of around 9% while each additional year of experience is associated with an increase of the premium of around 1.2 percentage points (about .7pp for the OLS case). It is worth noting that the married premium for those with zero experience is consistent with positive employer statistical discrimination. Without an instrument for marriage, however, we cannot rule out alternative drivers of this observed premium, such as selection bias.

In columns (4) and (8) we additionally include interactions between experience and the two hard-to-observe variables. The first point to note is that the coefficient on marriage and marriage interacted with experience do not change with these inclusions. At this point, we rule out employer learning as an explanation for the observed wage-marriage experience profiles. The second point to highlight is that the coefficient on the non-cognitive index remains essentially unchanged once we include a non-cognitive experience interaction, which indicates that the premium that men with higher non-cognitive traits (self-esteem and self-perceived agency) receive is realized immediately on entering the labor market and does

[6] In McConnell and Valladares-Esteban (2023) we explore several mechanisms to explore the (cross-sectional) marriage wage premium. Some of these mechanisms could explain the pattern we document in columns (3) and (7). One such example is within household specialization (Becker, 1985, 1993). The way in which this mechanism could generate the observed pattern is if married men specialize more in the labor market. This would mean that each period, married men would work more than their non-married counterparts, and thus accumulate more human capital by on-the-job learning. This would explain a steeper wage-experience gradient for married men.

not change with experience. Thus, these traits must be observable to employers. This is somewhat surprising. Finally, we find that there is no initial return to cognitive ability, but that these returns build over the working life. This suggests that employers do learn about our hard-to-observe ability measure, consistent with key papers in the core EL-SD literature (Altonji and Pierret, 2001; Pinkston, 2009; Arcidiacono et al., 2010).

Table 2: Symmetric Learning Model: Men

	OLS Potential Experience				**IV Actual Experience**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Married	0.229***	0.223***	0.134***	0.133***	0.217***	0.211***	0.092**	0.093**
	(0.026)	(0.026)	(0.040)	(0.039)	(0.027)	(0.026)	(0.040)	(0.040)
Married× Experience			0.007**	0.007***			0.012***	0.013***
			(0.003)	(0.003)			(0.004)	(0.004)
NC Index		0.030***	0.030***	0.046**		0.028**	0.028**	0.036*
		(0.011)	(0.011)	(0.020)		(0.011)	(0.011)	(0.019)
NC Index× Experience				–0.001				–0.001
				(0.001)				(0.002)
AFQT		0.068***	0.068***	0.028		0.065***	0.065***	0.019
		(0.014)	(0.014)	(0.023)		(0.014)	(0.014)	(0.023)
AFQT× Experience				0.003**				0.005**
				(0.002)				(0.002)
Adjusted R^2	0.312	0.329	0.330	0.331	0.317	0.333	0.332	0.333
Observations	7,703	7,703	7,703	7,703	7,703	7,703	7,703	7,703

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, tenure, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

For women (Table 3), the interpretation of the results is also equivalent between the OLS and IV estimates. In columns (1) and (5), we document a null effect of marriage on wages.[7]. Moving to columns (2) and (6) we find that non-cognitive and cognitive abilities both positively affect wages, with the impact of cognitive ability being approximately twice as large as that of our non-cognitive score. In Columns (3) and (7) we include an interaction between marriage and experience. This specification highlights that the null effect we document in columns (1) and (5) – the *average* premium to being married over the observed life-cycle – is, in fact, a composite of a penalty for married women with no labor market experience which evolves into a premium when experience increases. In particular, in column (7) we see that married women without experience earn around 12% less than their single counterparts while an extra year of experience increases their wages by around 1.3% percentage points. In columns (4) and (8) we include experience interactions with the hard-to-observe variables. The intercept of the returns to cognitive ability is positive and significant (0.071 in the OLS and 0.068 in the IV) while the interaction between the AFQT score and experience has a coefficient that is not statistically different from zero. We document an analogous pattern for the non-cognitive index. As it is the case for men, positive employer discrimination seems not to be a driver of the marriage wage premium for women. The coefficient associated with the interaction between marriage and experience is positive which is at odds with the existence of any type of positive employer discrimination that rationalizes a wage premium for married women. Nevertheless, it is relevant that the marriage wage premium of women is the reflection of an initial penalty that turns into a premium. In

[7]The median year in our data is 1989This is consistent with the null effect of being married on wages we document in McConnell and Valladares-Esteban (2023) for both a Heckman Selection Model, and an IV-Heckman Selection Model, for the period 1984-1990.

particular, this pattern is consistent with the presence of statistical discrimination based on traditional sex roles within (married) households. The idea is that, when employers observe a married female worker with no experience, they use marriage to proxy unobservables such us attachment to the labor force or willingness to work long hours that might be negatively related with the stereotypical role of a married woman. As the labor market experience of married women increases, we find that the initial penalty to being married becomes smaller and eventually becomes a premium. One mechanism that can explain the positive married-experience interaction term relates to the work of Pilossoph and Wee (2021), who propose a theory to explain the existence of a marriage wage premium for both husbands and wives. A key mechanism behind their work is of within-household income pooling, which would allow married woman to set a higher reservation wage during job search. The patterns we document for the wage-experience profile for married women indicates how a marriage wage premium for women can coexist with wage penalties based on traditional sex roles.

Table 3: Symmetric Learning Model: Women

	OLS Potential Experience				**IV Actual Experience**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Married	0.018	0.011	–0.134***	–0.134***	0.001	–0.005	–0.122***	–0.122***
	(0.032)	(0.031)	(0.039)	(0.039)	(0.033)	(0.033)	(0.038)	(0.038)
Married× Experience			0.014***	0.014***			0.013***	0.013***
			(0.004)	(0.004)			(0.005)	(0.005)
NC Index		0.039***	0.040***	0.044**		0.036***	0.037***	0.040**
		(0.013)	(0.012)	(0.021)		(0.012)	(0.012)	(0.020)
NC Index× Experience				–0.000				–0.000
				(0.002)				(0.002)
AFQT		0.081***	0.081***	0.071***		0.072***	0.072***	0.068***
		(0.013)	(0.013)	(0.022)		(0.013)	(0.013)	(0.021)
AFQT× Experience				0.001				0.000
				(0.002)				(0.002)
Adjusted R^2	0.243	0.269	0.273	0.273	0.276	0.296	0.298	0.298
Observations	6,383	6,383	6,383	6,383	6,383	6,383	6,383	6,383

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, tenure, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

3.3 Heterogeneity by Education

We conclude our analysis by investigating the extent to which employer learning and statistical discrimination may differ by education. Arcidiacono, Bayer, and Hizmo (2010) document that for male high school graduates, employers do not initially observe workers' AFQT, but that they learn about this as worker experience increases. For male college graduates there is no employer learning – employers factor in worker AFQT immediately on entry to the labor market. The authors suggest that for recent college graduates, the information on resumes – past test score, major, college attended may convey much of this information. Irrespective of the precise reason that employer learning occurs differently across education groups, the work of Arcidiacono, Bayer, and Hizmo (2010) suggests that it will likely be instructive to consider analysis of employer learning models by education groups.

3.3.1 Men

We start our analysis with men, splitting our core analysis sample into two groups – a high school sub-sample comprising those with a high school diploma or less, and a college sub-sample composed of those with at least some college. In Table 4 we present both OLS and IV results as before, again focusing more on the IV specifications. We start by documenting that the married coefficients in the column (5) specification are essentially identical across sub-samples. The coefficients on the two hard-to-observe variables, presented in column (6), mark a divergence between the two groups of workers. For the high school group, we find that both non-cognitive and cognitive measures are statistically significant, with a one standard deviation increase associated respectively with 3.5% and 6% percent higher wages. For college workers, cognitive measures are statistically significantly different from zero, yet we document a null effect for non-cognitive skills. The wage-experience profile estimates that we document for being married (in both columns (7) and (8)) are similar for both education groups, and follow the patterns that we show for the full sample. For the high school group we (i) do not find non-cognitive skills to be important in driving wages and (ii) find evidence of significant employer learning on cognitive ability. For the college group, non-cognitive and cognitive skills are both important factors in determining wages, but both are accounted for by employers immediately on workers' entry into the labor market – we find no employer learning. The AFQT wage-experience profiles we document across education groups for men are consistent with the work of Arcidiacono, Bayer, and Hizmo (2010).

Table 4: Symmetric Learning Model: Men, by Education Group

	OLS Potential Experience				IV Actual Experience			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
A.) High School								
Married	0.223***	0.216***	0.132***	0.131***	0.216***	0.209***	0.063	0.068
	(0.033)	(0.032)	(0.050)	(0.050)	(0.036)	(0.035)	(0.053)	(0.053)
Married× Experience			0.007*	0.007**			0.015***	0.016***
			(0.003)	(0.003)			(0.005)	(0.005)
NC Index		0.038***	0.038***	0.041*		0.035**	0.035**	0.021
		(0.013)	(0.013)	(0.024)		(0.014)	(0.014)	(0.024)
NC Index× Experience				–0.000				0.001
				(0.002)				(0.002)
AFQT		0.064***	0.063***	0.002		0.060***	0.060***	–0.006
		(0.015)	(0.015)	(0.024)		(0.015)	(0.015)	(0.025)
AFQT× Experience				0.005***				0.007***
				(0.002)				(0.002)
Adjusted R^2	0.199	0.228	0.229	0.232	0.179	0.206	0.196	0.195
Observations	4,948	4,948	4,948	4,948	4,948	4,948	4,948	4,948
B. College								
Married	0.249***	0.241***	0.123*	0.121*	0.238***	0.229***	0.099	0.098
	(0.045)	(0.044)	(0.065)	(0.065)	(0.045)	(0.044)	(0.065)	(0.065)
Married× Experience			0.011**	0.010**			0.014**	0.013**
			(0.005)	(0.005)			(0.006)	(0.006)
NC Index		0.010	0.011	0.055*		0.011	0.012	0.052*
		(0.018)	(0.018)	(0.033)		(0.018)	(0.018)	(0.032)
NC Index× Experience				–0.004				–0.004
				(0.002)				(0.003)
AFQT		0.045**	0.046**	0.074**		0.046**	0.047**	0.074**
		(0.019)	(0.019)	(0.033)		(0.019)	(0.019)	(0.032)
AFQT× Experience				–0.002				–0.003
				(0.002)				(0.002)
Adjusted R^2	0.314	0.320	0.322	0.324	0.321	0.327	0.327	0.331
Observations	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, tenure, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

3.3.2 Women

We present the results for women in Table 5. The patterns are broadly similar across specification for OLS and IV, although we lose statistical significance in some cases with our IV results. The results we document in column (5) – the null effect of being married on wages for women – mirrors what we find for our full sample analysis. When we move to column (6) we find that although the relationship between wages and AFQT are almost identical across education groups, we only find a significant effect of non-cognitive skills for college educated women. For women with a high school diploma or less, we find no impact of non-cognitive skills on wages. The wage-experience profiles we estimate in columns (7) and (8) are identical for both sub-groups. For the high school group, being married at the beginning of ones career is associated with a large and statistically significant penalty, yet the married-experience interaction is positive and statistically significantly different from zero. For the college group of women, there is a less pronounced effect of being married across the life-cycle. We find no evidence of employer learning for either of the hard-to-observe variables.

The most striking finding that we document in Table 5 is that unlike men, there appears to be little evidence of employer learning about cognitive ability for those without a college degree. For both educational groups, there is an initial premium to AFQT score at entry into the labor market, and no subsequent employer learning. Why should we find such a discrepancy across genders for employer learning by education group, if as Arcidiacono, Bayer, and Hizmo (2010) suggest, it is the resume of college educated workers that conveys much of the informational content of the AFQT? We leave this question unanswered in this paper, but it does suggest that other mechanisms could be at play behind the finding of Arcidiacono, Bayer, and Hizmo (2010), which we empirically corroborate in our work, that AFQT is difficult for employers to observe for men with a high school diploma, but not for college-educated men.

Table 5: Symmetric Learning Model: Women, by Education Group

	OLS Potential Experience				**IV Actual Experience**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
A.) High School								
Married	0.018	0.017	–0.182***	–0.183***	–0.001	–0.010	–0.152***	–0.152***
	(0.048)	(0.046)	(0.059)	(0.058)	(0.053)	(0.050)	(0.053)	(0.053)
Married× Experience			0.017***	0.017***			0.016**	0.016**
			(0.005)	(0.005)			(0.006)	(0.006)
NC Index		0.018	0.018	0.018		0.013	0.013	0.009
		(0.016)	(0.016)	(0.029)		(0.016)	(0.016)	(0.026)
NC Index× Experience				0.000				0.001
				(0.003)				(0.003)
AFQT		0.084***	0.084***	0.063**		0.070***	0.070***	0.048*
		(0.016)	(0.016)	(0.027)		(0.015)	(0.015)	(0.025)
AFQT× Experience				0.002				0.003
				(0.003)				(0.003)
Adjusted R^2	0.159	0.192	0.198	0.198	0.208	0.237	0.240	0.242
Observations	3,586	3,586	3,586	3,586	3,586	3,586	3,586	3,586
B. College								
Married	0.021	0.011	–0.091*	–0.091*	0.010	0.001	–0.085	–0.085
	(0.043)	(0.042)	(0.055)	(0.055)	(0.043)	(0.043)	(0.053)	(0.053)
Married× Experience			0.010*	0.010*			0.010	0.010
			(0.006)	(0.006)			(0.006)	(0.006)
NC Index		0.063***	0.063***	0.059**		0.063***	0.064***	0.059**
		(0.019)	(0.018)	(0.028)		(0.018)	(0.018)	(0.027)
NC Index× Experience				0.000				0.001
				(0.002)				(0.003)
AFQT		0.062***	0.062***	0.068***		0.062***	0.062***	0.070***
		(0.017)	(0.017)	(0.026)		(0.016)	(0.016)	(0.025)
AFQT× Experience				–0.001				–0.001
				(0.002)				(0.003)
Adjusted R^2	0.184	0.213	0.216	0.215	0.206	0.231	0.232	0.230
Observations	2,797	2,797	2,797	2,797	2,797	2,797	2,797	2,797

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, tenure, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

4 Conclusion

We extend the employer learning and statistical discrimination frameworks of Altonji and Pierret (2001) and Schönberg (2007) – Pinkston (2009) to the case of marriage to test the hypothesis that the marriage wage premium might be a consequence of employer discrimination. Although we document that individuals with higher cognitive and non-cognitive skills are more likely to be married and that employers learn about the hard-to-observe worker's skills, we find no evidence that married individuals are positively discriminated. In fact, we find that the marriage wage premium increases with labor market experience, the opposite of what discrimination implies.

We highlight that women's marriage premium is entirely driven by the interaction between marriage and experience, especially among women without a college education. The results we present are essential to understand the determinants of the marriage wage premium as they falsify one of the mechanisms discussed in the literature. In (McConnell and Valladares-Esteban, 2023), we provide an exhaustive analysis of the causal effect of being married on wages and a coherent set of mechanisms that can rationalize the marriage wage premium.

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Appendix

A On the Different Forms of Discrimination

Let us start by considering how the marriage wage premium comes about in a framework in which, given the same productivity, employers have a preference for married individuals. Although the taste-based discrimination is plausible proposition in other contexts, it does not fit well the case of marriage. First, marriage, unlike race or sex, is not an immutable characteristic. Hence, if employers were to have an animus towards single individuals, these could get married or simply pose as married. Secondly, the secular decline of marriage rates and the increase of the age of first marriage are at odds with a widespread discrimination of single individuals in the labor market, as these trends would have implied a significant individual economic cost in terms of wage penalties. Finally, as pointed out by Becker (1957), market competition is to erode taste-based discrimination as those employers who penalize single individuals incur an additional production cost. Therefore, we conclude that taste-based discrimination is not a plausible candidate to explain the marriage wage premium.

A different type of discrimination may arise based on firms beliefs about who in the household takes on the burden of home production. The framework here would be an extension of the model in Albanesi and Olivetti (2009) to allow firms' beliefs to be based not only on sex but also on marital status. The model in Albanesi and Olivetti (2009) can be described as follows. All agents are married and living in households with two spouses, one male and one female. Agents allocate their energy between home production and market work effort. Time devoted to home production increses the utility cost of providing work effort. Employers cannot observe how much a worker devotes to home production not their work effort. However, employers can monitor the worker's production. This informational friction leads to a problem of adverse selection and moral hazard. Firms solve the moral hazard problem by offerening a contract that links pay to production. At the same time, employers try to minimise adverse selection by offering different steepness of the performance pay based on the believed amount of home production hours of a worker as they know that the disutiliy of effort increases with home production hours. In other words, it is optimal for employers to offer a lower marginal return to output for workers that have higher home hours. Workers take as given the contracts offered by employers to determine the optimal allocation of home production hours and work effort. Albanesi and Olivetti (2009) show that if there is a widespread belief among employers that women devote more time to home production than their husbands, it is optimal for firms to offer women flatter performance contracts than those offered to men. Given the difference in contracts, married households find it optimal to actually allocate more home production hours to the wife than to the husband. This, in turn, generates a penalty for wives due to their higher home production hours. The wage gap appears in the model even when there are no differences in work productivity between sexes. In other words, if the widespread belief would be that husbands do more home production hours than wives, the wage penalty would symmetrically point to the opposite direction.

A natural extension to the Albanesi and Olivetti (2009) model is to include single men and women. Firms would have believes in two dimensions, sex and marital status. Based on the time allocation data, employers' beliefs would reflect the fact that married women devote more hours to home production than their single counterparts, providing a plausible explanation for a marriage penalty. The same logic would apply to men, as married men devote more time to home production than their single counterpats. Therefore, this type of discrimination based on firms belief might serve as a partial explanation for the women's married penalty observed before the 1990s but cannot be put forward as an rational for the marriage wage premium we see nowadays for both men and women.

In sum, the only plausible form of discrimination able to rationalize a marriage wage premium for both men and women is statistical discrimination in a context in which individuals with hard-to-observe characteristics that are positively related to productivity are more likely to be married.

B Additional Results

B.1 Factor Loadings for Non-Cognitive Index

Table A1: Factor Loadings for Non-Cognitive Index

	(1)	(2)
	Men	**Women**
Rotter Locus of Control (1979)	-.293	-.319
Rosenburg Self-Esteem Scale (1980)		
Q1: I am a person of worth	.611	.579
Q2: I have a number of good qualities	.648	.631
Q3*: I am inclined to feel that I am a failure	.672	.65
Q4: I am able to do things as well as most other people	.597	.567
Q5*: I felt I do not have much to be proud of	.635	.637
Q6: I take a positive attitude toward myself	.658	.644
Q7: I am satisfied with myself	.524	.565
Q8*: I wish I could have more respect for myself	.433	.529
Q9*: I certainly feel useless at times	.496	.522
Q10*: At times I think I am no good at all	.556	.58

Notes: * denotes that for this question we reversed the direction of the scale in order to score all Rosenburg questions in the same direction: a higher score means higher self-esteem. All Rosenburg questions are on a 1-4 scale. The Rotter Locus of Control scale is based on 4 individual questions, each of which are on a 1-4 scale. We use the combined score here, as provided in the NLSY data, which takes values 4-16. The factor model is estimated via Maximum Likelihood. The factor loadings are based on an orthogonal varimax rotation. Data used: NLSY79.

B.2 Summary Statistics

Table A2: Descriptive Statistics, EL-SD Sample
Means, Standard Deviations in Parentheses

	(1) Men	**(2) Women**
Sample Size	7,703	6,383
Number of Individuals	1,303	1,323
Married	0.662	0.755
Ever Observed Married in Panel	0.718	0.820
Hourly Wage (2006 Dollars)	17.35	12.97
	(9.47)	(6.42)
Job Tenure	3.33	3.19
	(3.43)	(3.42)
Experience	10.04	8.60
	(5.24)	(4.98)
Potential Experience	12.62	11.28
	(5.44)	(5.20)
Age	30.44	29.37
	(5.55)	(5.28)
Highest Level of Education:		
HS Dropout	0.120	0.050
HS Graduate	0.533	0.531
Some College	0.177	0.240
College Graduate	0.126	0.133
Advanced Graduate	0.045	0.046
Urban Residence	0.715	0.719
Number Children, 0–4	0.476	0.439
	(0.707)	(0.643)
Number Children, 5–17	0.430	0.501
	(0.783)	(0.826)
Children, 18 and over	0.004	0.005

Notes: Data used: NLSY79, 1981-2012.

B.3 Marriage, AFQT and Non-Cognitive Measures

Table A3: Non-Cognitive Index, AFQT and Later Marital Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Men			Women		
	Non-Cognitive Index Only	Cognitive Measure Only	Both Measures	Non-Cognitive Index Only	Cognitive Measure Only	Both Measures
A. Full Sample						
Non-Cognitive Index	0.039***		0.037***	0.019*		0.015
	(0.010)		(0.011)	(0.011)		(0.011)
AFQT Score		0.027**	0.020		0.039***	0.036***
		(0.013)	(0.013)		(0.014)	(0.014)
$\overline{Y}$	0.557	0.557	0.557	0.628	0.628	0.628
Adjusted R^2	0.133	0.130	0.134	0.087	0.089	0.090
Observations	16,562	16,562	16,562	13,997	13,997	13,997
B. High School						
Non-Cognitive Index	0.051***		0.047***	0.022		0.016
	(0.015)		(0.016)	(0.018)		(0.018)
AFQT Score		0.034*	0.024		0.037**	0.033*
		(0.018)	(0.018)		(0.018)	(0.019)
$\overline{Y}$	0.566	0.566	0.566	0.684	0.684	0.684
Adjusted R^2	0.129	0.123	0.131	0.077	0.079	0.080
Observations	8,405	8,405	8,405	6,088	6,088	6,088
C. College						
Non-Cognitive Index	0.035**		0.033**	0.018		0.015
	(0.014)		(0.014)	(0.014)		(0.014)
AFQT Score		0.033*	0.029		0.053***	0.052***
		(0.020)	(0.020)		(0.019)	(0.020)
$\overline{Y}$	0.547	0.547	0.547	0.585	0.585	0.585
Adjusted R^2	0.169	0.167	0.170	0.125	0.130	0.130
Observations	8,157	8,157	8,157	7,909	7,909	7,909

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The following controls are included: dummies for highest level of educational attainment, a dummy for urban residence, region in 1979 dummies, cohort dummies, year dummies, maternal education, paternal education, dummies based on the following measures when respondent was 14: father worked, mother worked, father absent, mother absent, household received newspapers, household had a library card. Non-cognitive index is a single factor based on 10 self-esteem questions (Rosenberg Self-Esteem Scale, questions administered in 1980) and the Rotter Locus of Control Scale (administered in 1979). Both the non-cognitive index and the AFQT measure are standardized. Data used: NLSY79, 1981-2012.

C Asymmetric Employer Learning

C.1 Empirical Specification

Formally, we extend the specification from Equation 1:

$$
\begin{aligned}
y_i = {} & \alpha_0 M_i + \alpha_1 (M_i \times x_i) + \alpha_2 (M_i \times t_i) \\
& + \beta_0 A_i + \beta_1 (A_i \times x_i) + \beta_2 (A_i \times t_i) \\
& + \delta_0 NC_i + \delta_1 (NC_i \times x_i) + \delta_2 (NC_i \times t_i) + C_i^{'} \gamma + \epsilon_i .
\end{aligned} \tag{2}
$$

We now include three interactions terms in tenure (t_i) in addition to those in experience (x_i). The vector C_i is also augmented to include polynomials of tenure up to order three to mirror our controls for experience.

Analogously to the concerns about the potential relationship between experience and productivity, tenure might also be correlated with unobserved productivity, thus biasing the tenure interaction terms. We adapt the approach in Pinkston (2009) to instrument for tenure. Specifically, we regress tenure in period t on actual experience, full duration of current tenure spell, and career-average tenure spells. The career-average tenure spells is a measure that encapsulates individuals' propensity to stay in a job over their (observed) careers and their general ability to enter well-matched jobs. In addition, the full duration of current job spell should capture firm-worker match-specific elements that may be correlated with the residual in the wage equation.[8] To the extent that these variables capture the channels through which tenure is correlated with the residual in Equation 2, we can use the residual from this regression as an instrument for tenure.

C.2 Results

Table B1 presents the results for men. The conclusions regarding public learning from Table 2 are robust to the inclusion of tenure. That is, the interaction between AFQT and experience in columns (4) and (8) remains positive, indicating there exists public learning. The non-cognitive index coefficient is statistically significant. Both the experience and the tenure interactions are as good as zero. The interaction between marriage and experience is also positive, which indicates that there is no employer learning based on marital status.

Table B2 presents the estimates for women. The inclusion of tenure enriches the inference that we draw form Table 3 but do not modify the main conclusion. In the IV results, we document a non-cognitive index coefficient of .035 in column (7). Once we allow for an interaction between tenure and the non-cognitive index, as we do in column (8), we find evidence of private employer learning that is consistent with employers observing non-cognitive skills at the start of the job spell, and the relative importance of this non-cognitive measure declining with the job spell. This raises the possibility that employers are statistically discriminating on non-cognitive traits – traits that we originally believed to be hard-to-observe – in order to learn about other aspects of worker productivity over the job spell. There is no evidence of any public learning on either of the skill measures. The interaction between being married and experience and the interaction between being married and tenure confirm the composition of the MWP for women described in Section 3.2. Married women start their careers experiencing a wage

[8] The regression output is summarized as follows:

$$
\begin{array}{ll}
\text{Men: } t_i = \underset{(0.082)}{-1.102} + \underset{(0.018)}{0.116}\ \bar{t}_i^{career} + \underset{(0.006)}{0.176}\ dur_i + \underset{(0.005)}{0.230}\ x_i + \hat{e}_i\ , & \text{Adjusted } R^2 : 0.448 \\
\text{Women: } t_i = \underset{(0.078)}{-0.787} + \underset{(0.019)}{0.064}\ \bar{t}_i^{career} + \underset{(0.007)}{0.192}\ dur_i + \underset{(0.006)}{0.234}\ x_i + \hat{e}_i\ , & \text{Adjusted } R^2 : 0.478
\end{array}
$$

Table B1: Asymmetric Learning Model: Men

	OLS Potential Experience Actual Tenure				IV Actual Experience Actual Tenure			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Married	0.221***	0.215***	0.134***	0.132***	0.220***	0.212***	0.109***	0.109***
	(0.026)	(0.026)	(0.039)	(0.039)	(0.028)	(0.027)	(0.041)	(0.041)
Married× Experience			0.007**	0.007**			0.013***	0.013***
			(0.003)	(0.003)			(0.004)	(0.004)
Married× Tenure			–0.000	–0.000			–0.007	–0.008
			(0.007)	(0.007)			(0.007)	(0.007)
NC Index		0.030***	0.031***	0.045**		0.027**	0.027**	0.035*
		(0.011)	(0.011)	(0.019)		(0.011)	(0.011)	(0.020)
NC Index× Experience				–0.001				–0.002
				(0.001)				(0.002)
NC Index× Tenure				–0.001				0.003
				(0.003)				(0.003)
AFQT		0.066***	0.066***	0.026		0.067***	0.067***	0.026
		(0.014)	(0.014)	(0.023)		(0.014)	(0.014)	(0.023)
AFQT× Experience				0.004**				0.005**
				(0.002)				(0.002)
AFQT× Tenure				–0.003				–0.002
				(0.003)				(0.003)
Adjusted R^2	0.321	0.337	0.338	0.339	0.286	0.313	0.315	0.315
Observations	7,703	7,703	7,703	7,703	7,703	7,703	7,703	7,703

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in both tenure and experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all tenure terms are instrumented using the approach outlined in section C.1, and experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

penalty with respect to their single counterparts. As their career progresses, this penalty becomes a premium.

Table B2: Asymmetric Learning Model: Women

	OLS Potential Experience Actual Tenure				IV Actual Experience Actual Tenure			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Married	0.010	0.004	–0.126***	–0.124***	–0.014	–0.019	–0.094**	–0.092**
	(0.031)	(0.031)	(0.039)	(0.039)	(0.034)	(0.034)	(0.043)	(0.044)
Married× Experience			0.006	0.006			0.012**	0.012**
			(0.004)	(0.004)			(0.005)	(0.006)
Married× Tenure			0.019**	0.020**			–0.008	–0.010
			(0.008)	(0.008)			(0.010)	(0.010)
NC Index		0.038***	0.039***	0.041**		0.034***	0.035***	0.062***
		(0.012)	(0.012)	(0.020)		(0.013)	(0.013)	(0.023)
NC Index× Experience				–0.001				0.001
				(0.002)				(0.003)
NC Index× Tenure				0.002				–0.012**
				(0.003)				(0.005)
AFQT		0.079***	0.079***	0.064***		0.078***	0.078***	0.069***
		(0.013)	(0.013)	(0.021)		(0.014)	(0.014)	(0.024)
AFQT× Experience				–0.000				–0.001
				(0.002)				(0.003)
AFQT× Tenure				0.005				0.007
				(0.003)				(0.004)
Adjusted R^2	0.261	0.286	0.291	0.292	0.068	0.119	0.123	0.119
Observations	6,383	6,383	6,383	6,383	6,383	6,383	6,383	6,383

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in both tenure and experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all tenure terms are instrumented using the approach outlined in section C.1, and experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

C.3 Heterogeneity by Education

We once again run our analysis by education group. We present the results for men in Table B3. We do not learn anything new from the asymmetric learning model in this case, as there is no evidence of private learning for any of our three main variables (married, ability, non-cognitive index) for men, be they in the high school or the college sub-samples.

We present the asymmetric learning results by education group for women in Table B4. The key finding of note from this analysis can be seen in column (8). Here we see that the wage-non-cognitive tenure profile (high initial wage returns, declining with the job spell) that we document in Table B2 are being driven exclusively by the college educated women. We are not able to explain this result, but flag it here for future research.

Table B3: Asymmetric Learning Model: Men, by Education Group

	OLS Potential Experience Actual Tenure				IV Actual Experience Actual Tenure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A.) High School								
Married	0.211***	0.205***	0.130***	0.128***	0.228***	0.217***	0.078	0.079
	(0.033)	(0.032)	(0.048)	(0.048)	(0.041)	(0.039)	(0.055)	(0.055)
Married× Experience			0.004	0.005			0.016**	0.017**
			(0.004)	(0.004)			(0.007)	(0.007)
Married× Tenure			0.007	0.007			–0.006	–0.007
			(0.008)	(0.008)			(0.010)	(0.010)
NC Index		0.037***	0.037***	0.042*		0.034**	0.034**	0.018
		(0.013)	(0.013)	(0.024)		(0.014)	(0.014)	(0.026)
NC Index× Experience				0.000				0.000
				(0.002)				(0.002)
NC Index× Tenure				–0.002				0.004
				(0.003)				(0.004)
AFQT		0.062***	0.062***	0.000		0.062***	0.062***	0.002
		(0.015)	(0.015)	(0.024)		(0.015)	(0.015)	(0.026)
AFQT× Experience				0.005***				0.008***
				(0.002)				(0.003)
AFQT× Tenure				–0.003				–0.005
				(0.003)				(0.004)
Adjusted R^2	0.212	0.240	0.241	0.244	0.096	0.156	0.153	0.153
Observations	4,948	4,948	4,948	4,948	4,948	4,948	4,948	4,948
B. College								
Married	0.246***	0.239***	0.126**	0.126*	0.234***	0.225***	0.116*	0.114*
	(0.044)	(0.044)	(0.064)	(0.064)	(0.045)	(0.044)	(0.066)	(0.066)
Married× Experience			0.015**	0.014**			0.014**	0.015**
			(0.006)	(0.006)			(0.007)	(0.007)
Married× Tenure			–0.019	–0.020			–0.011	–0.013
			(0.012)	(0.013)			(0.013)	(0.013)
NC Index		0.012	0.011	0.052*		0.013	0.013	0.050
		(0.018)	(0.018)	(0.032)		(0.019)	(0.018)	(0.032)
NC Index× Experience				–0.003				–0.004
				(0.003)				(0.003)
NC Index× Tenure				–0.001				0.001
				(0.005)				(0.005)
AFQT		0.042**	0.042**	0.072**		0.047**	0.047**	0.080**
		(0.019)	(0.019)	(0.032)		(0.020)	(0.019)	(0.033)
AFQT× Experience				–0.002				–0.004
				(0.003)				(0.003)
AFQT× Tenure				–0.004				0.003
				(0.005)				(0.006)
Adjusted R^2	0.318	0.324	0.328	0.329	0.307	0.317	0.320	0.323
Observations	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in both tenure and experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all tenure terms are instrumented using the approach outlined in section C.1, and experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.

Table B4: Asymmetric Learning Model: Women, by Education Group

	OLS Potential Experience Actual Tenure				IV Actual Experience Actual Tenure			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
A.) High School								
Married	0.006	0.004	–0.158***	–0.154***	–0.023	–0.028	–0.095	–0.102
	(0.047)	(0.045)	(0.056)	(0.057)	(0.054)	(0.050)	(0.064)	(0.064)
Married× Experience			0.008	0.008			0.015*	0.016**
			(0.005)	(0.005)			(0.008)	(0.008)
Married× Tenure			0.019*	0.020*			–0.019	–0.019
			(0.011)	(0.011)			(0.014)	(0.013)
NC Index		0.019	0.019	0.028		0.008	0.008	0.015
		(0.016)	(0.016)	(0.028)		(0.016)	(0.016)	(0.031)
NC Index× Experience				–0.001				0.002
				(0.003)				(0.004)
NC Index× Tenure				–0.001				–0.008
				(0.005)				(0.006)
AFQT		0.081***	0.082***	0.046*		0.079***	0.078***	0.065*
		(0.015)	(0.015)	(0.025)		(0.016)	(0.016)	(0.033)
AFQT× Experience				0.002				0.001
				(0.003)				(0.004)
AFQT× Tenure				0.005				0.002
				(0.004)				(0.006)
Adjusted R^2	0.189	0.220	0.226	0.227	.	0.006	0.015	0.009
Observations	3,586	3,586	3,586	3,586	3,586	3,586	3,586	3,586
B. College								
Married	0.017	0.007	–0.090*	–0.091*	0.000	–0.008	–0.072	–0.057
	(0.042)	(0.041)	(0.055)	(0.053)	(0.045)	(0.045)	(0.059)	(0.058)
Married× Experience			0.004	0.004			0.007	0.007
			(0.007)	(0.007)			(0.008)	(0.008)
Married× Tenure			0.020	0.019			0.001	–0.004
			(0.012)	(0.012)			(0.015)	(0.016)
NC Index		0.062***	0.063***	0.045*		0.067***	0.068***	0.090***
		(0.018)	(0.018)	(0.027)		(0.019)	(0.019)	(0.031)
NC Index× Experience				0.000				0.002
				(0.003)				(0.004)
NC Index× Tenure				0.005				–0.013**
				(0.004)				(0.007)
AFQT		0.061***	0.060***	0.067***		0.065***	0.065***	0.065**
		(0.017)	(0.017)	(0.026)		(0.018)	(0.018)	(0.028)
AFQT× Experience				–0.003				–0.003
				(0.003)				(0.003)
AFQT× Tenure				0.008**				0.007
				(0.004)				(0.005)
Adjusted R^2	0.196	0.224	0.229	0.232	0.032	0.070	0.072	0.069
Observations	2,797	2,797	2,797	2,797	2,797	2,797	2,797	2,797

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. Standard errors are reported in parentheses, where these are clustered by individual. The dependent variable in all columns is the natural log of wages in 2006 Dollars. The following additional control variables are included in all specifications: dummies for highest level of educational attainment, the education dummies interacted with a linear time trend, the number of children below the age of 5, the number of children aged 5-17, and a dummy for a child over the age of 18, a dummy for urban residence, year dummies, and cubic polynomials in both tenure and experience. Results from a pooled OLS model with experience captured by potential experience are presented in Columns 1-4. Results from an IV model where all tenure terms are instrumented using the approach outlined in section C.1, and experience terms are actual experience instrumented by potential experience are presented in Columns 5-8. Data used: NLSY79, 1981-2012.