WORKING PAPER #439
PRINCETON UNIVERSITY
INDUSTRIAL RELATIONS SECTION
JUNE 2000
http://www.irs.princeton.edu/pubs/working_papers.html

Do Marital Status and Computer Usage Really Change the Wage Structure? Evidence from a Sample of Twins¹

Harry A. Krashinsky
Department of Economics
Princeton University

May 30, 2000

¹I would like to thank Orley Ashenfelter and Cecilia Rouse for providing me with both data for this analysis and helpful comments and suggestions. I would also like to thank participants of the Princeton Labor Lunch seminar series for their comments. I gratefully acknowledge financial support from the Alfred P. Sloan Foundation. All errors are my own.

Abstract

Both marital status and computer usage on the job have been found to increase earnings by as much as two additional years of schooling. If correct, these findings suggest that factors other than long-term human capital investments are key determinants of earnings. Data on identical twins are used in this paper to sweep out selection effects and examine the effect of marital status and computer usage on wages. Within-twin estimates indicate that, unlike education, job tenure and union status, neither marital status nor computer usage have a large or significant effect on wages.

1 Introduction

Although schooling and experience are now well established as key determinants of worker earnings,¹ considerable statistical evidence has begun to suggest that other factors are equally influential determinants of earnings. Both marital status² and computer usage³ are typically found to increase earnings by as much as 20 percent or more for males. Taken at face value, these estimates imply that marriage alone, or learning to use a computer, will raise earnings more than two additional years of schooling. If correct, these findings suggest that factors other than long term human capital investments are key determinants of earnings. Perhaps because of their size, some researchers have begun to question whether factors such as computer usage and marital status are really causal determinants of earnings, or whether they instead reflect omitted variables, such as intelligence, appearance, or family background, that happen to be correlated with earnings.

In this paper I use a sample of monozygotic (genetically identical) twins to measure the extent to which marital status, computer usage, union status, tenure on the job, and schooling are correlated with earnings independent of family background effects. Correlations of within-twin contrasts in these variables with contrasts in earnings measure the extent to which non-genetic or family background factors are responsible for earnings differences, while correlations of average values of these characteristics with average earnings across families measure pure selection effects. To account for the problem of the exacerbated measurement error known to affect within-family contrasts I construct reliability measures for all the determinants of earnings and conduct the analysis using a generalized method of moments estimation procedure. The

¹Early work by Mincer (1958), Ben-Porath (1967) and Griliches (1970) outlines the importance of human capital as a determinant of earnings has been expanded upon by many authors using both within-sibling comparisons and instrumental variables methods in recent years. For surveys of this work, see Ashenfelter, Harmon, and Oosterbeek (1999), Card (1999), and Angrist and Krueger (1999).

²Studies by Korenman and Neumark (1991) and Loh (1996) consider the strong significance of this variable and also contain surveys of prior work on this subject.

³See especially Krueger (1993), but also: Boozer, Krueger and Wolkon (1992); Autor, Katz and Krueger (1998).

empirical results indicate that schooling and job tenure are important causal determinants of earnings, but that marital status and computer usage are not.

The remainder of the paper is structured as follows: The first section presents a brief literature review of prior work on typical regressors in the wage equation, an explanation of the estimation procedure and highlights the importance of accounting for measurement error in the estimation. The second section discusses the data and their limitations, and provides estimates of reliability for schooling, job tenure, marital status, computer usage, and union status. The third section reports the main empirical results.

2 Motivation and Econometric Framework

Table 1 contains a brief survey of a number of recent estimates of the effects of schooling, job tenure, marital status and computer usage on wages. In each case, the variable in question has a significant positive effect on the wage rate that is statistically significant and often of a considerable quantitative magnitude. Some of these findings are so robust that they have been used to test theoretical propositions about wage determination.⁴ A nagging doubt remains, however, that the strong effects of some of these variables on earnings may be a result of selection effects, suggesting that they may instead simply signal an omitted ability bias or other important determinants of earnings.

2.0.1 Estimation Procedure

One useful procedure for providing evidence on the magnitude of selection contrasts twins who share identical genes and also have very similar family backgrounds. Assuming that ability has a linear effect on earnings, the earnings equations for each twin can be expressed as follows:

$$\begin{aligned} y_{1j} &= \beta'_{1j} X_{1j} + \alpha' Z_j + A_j + \varepsilon_{1j} \\ y_{2j} &= \beta'_{2j} X_{2j} + \alpha' Z_j + A_j + \varepsilon_{2j} \end{aligned} \tag{1}$$

⁴For example, marital status has been studied by Becker; schooling by Card; tenure by Topel; computer use by Krueger.

where X_{ij} represents a vector of individual characteristics for twin i from family j , Z_j represents common characteristics for family j , A_j is a family-specific ability term and ε_{ij} is an individual-specific error term. If A_j is correlated with X_{ij} , the model can be further extended to allow for this correlation:

$$A_j = \gamma \left(\frac{X_{1j} + X_{2j}}{2} \right) + v_j \quad (2)$$

which leads to the reduced-form correlated random-effects model⁵:

$$\begin{aligned} y_{1j} &= \beta X_{1j} + \alpha Z_j + \gamma \left(\frac{X_{1j} + X_{2j}}{2} \right) + v_j + \varepsilon_{1j} \\ y_{2j} &= \beta X_{2j} + \alpha Z_j + \gamma \left(\frac{X_{1j} + X_{2j}}{2} \right) + v_j + \varepsilon_{2j} \end{aligned} \quad (3)$$

where γ represents the correlation between a family's ability level and each twin's individual characteristics. An attractive component of this model is that it provides estimates of both γ , the effect of family-related characteristics on wages, and β , the unbiased effect of individual-specific variables on earnings.

An alternative estimation procedure that accounts for familial ability bias is the fixed-effects model, which differences the two regressions used the correlated random effects model. The resulting equation is:

$$(y_{1j} - y_{2j}) = \beta(X_{1j} - X_{2j}) + (\varepsilon_{1j} - \varepsilon_{2j}) \quad (4)$$

Although this model derives estimates that are not correlated with ability⁶, it does not provide a direct estimate of the correlation between ability and individual variables, γ .

2.0.2 Within-Twin Omitted Variables

A potential criticism of this analysis relies upon within-twin differences in ability. Some authors⁷ have argued that there may be a positive correlation between the individual-specific component of ability, ε_{ij} , and the regressors, X_{ij} , which leads to a classical omitted variable bias. It has thus been suggested that

⁵See Chamberlain (1982). Due to inter-twin error correlation, a stacked GLS estimation procedure is used in this framework.

⁶Estimates derived from the fixed effects and correlated random effects models are identical because both estimation procedures provide consistent estimates of β .

⁷Neumark (1999) and Bound and Solon (1999), for example.

the within-twin estimates are upper-bounds of the relevant causal coefficients. Although this critique may weaken conclusions drawn about coefficients found to be significant in the within-twin framework, it also has strong implications for insignificant coefficients generated by this estimation approach. Specifically, this suggests that variables with insignificant fixed-effect coefficients can not have a positive effect on wages, implying that estimated effects of both marital status and computer usage at work presented below are upper bounds.

2.1 Measurement Error

The particular importance of accounting for measurement error in this econometric framework has been discussed by many authors⁸. In principle, measurement error can have substantial effects on all the regressors in a model, and careful inference requires that the model be modified to allow for measurement error in all of the explanatory variables. Specifically, if all of the observed explanatory variables, X , are measured with error, U , then the regressors of the model may be expressed as follows:

$$X_{1j} = X_{1j}^* + U_{1j} \text{ and } X_{2j} = X_{2j}^* + U_{2j}$$

where X_{ij}^* is the unobserved true value of X_{ij} that is unaffected by measurement error. Furthermore, the within-twin differenced variables can be expressed in a similar manner:

$$\begin{aligned} \Delta X_j &= X_{1j} - X_{2j} \\ &= \Delta X_j^* + \Delta U_j \end{aligned}$$

Assuming that the measurement error for the one twin is uncorrelated with the true value of X for the other twin, and assuming that any measurement error in the earnings variable is uncorrelated with both the independent variables and the measurement error associated with these variables, then the measurement-

⁸For example, Ashenfelter and Krueger (1994) and Griliches (1979) both discuss the importance of measurement error in the school regressor. See also Deaton (1985) and Fuller (1975).

error-corrected OLS estimator ($\tilde{b}_{OLS}$) and correlated random effects (CRE) estimator ($\tilde{b}_{CRE}$) are:

$$\tilde{b}_{OLS} = \tilde{b}_{CRE} = [X'X + n\Sigma]^{-1} X'y$$

where: X and y are the matrices formed by the components X_{ij} and y_{ij} , respectively; n is the sample size; and Σ is the variance-covariance matrix of the measurement error matrix, U . The measurement-error-corrected fixed-effects estimator uses a similar formula:

$$\tilde{b}_{FE} = [\Delta X' \Delta X + 2n\Sigma]^{-1} \Delta X' \Delta y_j$$

where ΔX and Δy are the respective within-twin-differenced analogs of X and y . Accounting for the matrix Σ is thus important for providing unbiased coefficient estimates, and it is also necessary to properly compute the standard errors of the regression coefficients.⁹ As such, various studies on the reliability of certain variables are critical to obtain credible estimators in this model.

3 The Data

The data set of identical twins was collected during the summers of 1991, 1992, 1993 and 1995 at the Twinsburg Twins Festival in Twinsburg, Ohio, and the interview questions were modeled after those in the Census and CPS instruments. Some of the data from the first three waves of this survey were used by Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998), who provide a discussion of the procedures used to collect this data. Some additional questions were specifically designed for interviewing twins. The data used in this study is drawn from the sub-sample of identical white twins¹⁰, both of who have worked within two years prior to the interview and are living within the United States. For those twins interviewed more than once, their responses were averaged over the years in which they were interviewed.

⁹Appendix 1 contains measurement-error corrected standard error formulas.

¹⁰The sample of white twins was selected to avoid convoluting the analysis with the anomolous sub-sample of black twins. Ashenfelter and Rouse (1998) document the fact that the coefficient on a indicator variable for black twins is positive in a regression on the pooled sample of twins, suggesting that the black sub-sample of twins may not be represent ative of the general population.

Table 2 displays the characteristics of the twins sample, and compares it to other salient aspects of white workers from related CPS supplements. On average, the data set composed of identical twins is generally better-educated and higher-paid than the general population. There are also fewer married individuals in the sample of twins than in the general population, but most of the other characteristics of the identical twins are relatively similar to those of the general population. To determine what effects these differences may have on a statistical analysis of the twins data set, Table 3 reports the estimates of earnings equations using the identical twins data set and the CPS. The results in this table demonstrate that the coefficient estimates for the identical twins sample are reasonably close to those from the CPS – every coefficient in the twins sample is of the same sign as those from the CPS samples, and all but the union status coefficient are of a larger magnitude. This suggests the possibility that the CPS contain more measurement error than the twins data, but generally, the results from Table 3 indicate that the two data sets provide similar basic information.

3.1 Reliability Estimates

To account for the possibility of measurement error in the twins data, I constructed the matrix of measurement error variances and covariances, Σ , from various studies that have examined the level of measurement error in particular variables. The matrix is displayed in Table 4. To derive the measurement error for the indicator variables in this matrix (marital and union status), I relied upon misclassifications detected in reinterviews of survey respondents. For example, an estimate of the reporting error for marital status is taken from a reinterview of Census respondents in the CPS in 1970. The cross-tabulation with an individual’s reported Census status and their reported CPS status is replicated in Tables 4a and 4b. Unfortunately, it is impossible to know how the mismatches in records are generated – the both the Census and CPS records could be subject to reporting error. As a simplifying assumption, I will assert that the probability of misclassification is identical for both matching records.¹¹ Thus, the misclassification error,

¹¹This is the working assumption of Card (1996) in his analysis of measurement error in union status.

$u_{married}$, could take on three possible values:

= 1 if the respondent is improperly classified as being married

$u_{married} = 0$ if there is no misclassification error

= -1 if the respondent is improperly classified as being non-married

Since it is not possible to know whether or not a discrepancy between the CPS and Census records is caused by an error of value 1 or -1, I pursue a conservative estimation strategy by considering the case that maximizes the variance of the measurement error¹², which yielded a measurement error variance of 0.013 for marital status¹³. This approach is equally valid with the union status variable, and using results in Table 4c from Freeman's (1984) work with the matched May 1979 "Dual Job" and "Pension" supplements of the CPS (both of which asked respondents if their jobs were covered by a collective bargaining agreement) a measurement error variance of 0.032 was calculated for union status.

¹²The specification that maximizes the variance of the measurement error which can be determined from the definition of variance:

$$V(u_{married}) = E(u_{married}^2) - E(u_{married})^2$$

Because the only non-zero values of the error term are -1 and 1, $E(u_{married}^2)$ is independent of assumptions about the specific value of the error. To illustrate this point, let the sample size be denoted as N , the total number of misclassifications as m , and the total number of misclassifications resulting from errors $u_{married} = 1$ as m_+ . Then the expected value of the squared error term is:

$$E(u_{married}^2) = \left(\frac{m_+}{N}\right) (1)^2 + \left(\frac{m - m_+}{N}\right) (-1)^2 = \frac{m}{N}$$

Thus, the expected value of the squared error is independent of the number of positive or negative errors, and is only dependent upon the *total* number of misclassifications. As such, maximizing the variance requires that $E(u_{married})$ is minimized, a term which is not independent of the number of positive or negative errors:

$$E(u_{married}) = \left(\frac{m_+}{N}\right) (1) + \left(\frac{m - m_+}{N}\right) (-1) = \frac{2m_+ - m}{N}$$

A minimization of this term requires that; $m_+ = 0.5m$, or that there are an equal number of positive and negative error terms. And in this case, the maximum possible variance is $\frac{m}{N}$.

¹³Refer to Appendix 2 for a more detailed derivation of the measurement error variance for all the regressors in this analysis.

To obtain estimates of the reporting error for years of tenure, Duncan's and Hill's (1985) cross-tabulations of employee survey data and employer records collected from a large manufacturing firm are used. They report that the ratio of the measurement error variance to the true variance for years of tenure is 0.011, and the variance of years of tenure is 78.76. Thus, if the true years of tenure are denoted as T^* , where $T = T^* + u_{tenure}$, then the variance of the response error on years of tenure, u_{tenure} , is 0.857.

Accounting for the measurement error in years of education can be accomplished by following Ashenfelter and Krueger's (1994) method of using the own-reported and sibling-reported measures of education in the data set of identical twins. Let the "true" level of education for twin i in family j be denoted as E_{ij}^* , and let both "own-reported" education for twin i in family j , E_{ij} , and the sibling-reported level of education for twin i in family j , $\tilde{E}_{ij}$, be measured with error, so that:

$$\begin{aligned} E_{ij} &= E_{ij}^* + \eta_{ij} \\ \tilde{E}_{ij} &= E_{ij}^* + \tilde{\eta}_{ij} \end{aligned}$$

where it is assumed that: $E(\eta_{ij}) = E(\tilde{\eta}_{ij}) = 0$ and $cov(\eta_{ij}, \tilde{\eta}_{ij}) = 0$. This implies that:

$$cov(E_{ij}, \tilde{E}_{ij}) = cov(E_{ij}^* + \eta_{ij}, E_{ij}^* + \tilde{\eta}_{ij}) = V(E_{ij}^*)$$

Then an estimate of the measurement error in years of education can be obtained from the following equation:

$$\begin{aligned} V(\eta_{ij}) &= V(\tilde{\eta}_{ij}) = V(E_{ij}) - V(E_{ij}^*) \\ &= V(E_{ij}) - cov(E_{ij}, \tilde{E}_{ij}) \\ &= 4.18 - 3.87 = 0.31 \end{aligned}$$

To accommodate measurement error in the dummy variable accounting for the use of computers at the respondent's job, it was not possible to consult prior validation studies, because none exist to the best of my knowledge. As such, an array of measurement error variance in this variable was considered, ranging from 0.02 to 0.1. Though arbitrarily defined, these two bounds seem to represent a reasonable scope of the possible reporting error in this variable, because the measurement error variance of other indicator variables

(such as marital status or union status) is in the low end of this range. Selecting an upper bound of 0.1 (an estimate of reporting error variance that is well above that of any other indicator variables) allows for a conservative estimate of the effect of measurement error on the computer-use variable.

4 Empirical Results

The results in table 5 demonstrate the effect of controlling for familial ability in an earnings equation both with and without corrections for measurement error. If familial ability had no effect on earnings, then an ordinary least-squares estimation procedure would provide an unbiased estimator of the effect of the exogenous regressors and the ordinary least squares and correlated random effects estimator would differ only because of sampling error. As is apparent from Table 5, however, the coefficients of marital status differ dramatically with the estimation procedure.¹⁴ Without controls for ability, marital status raises wages by 20% for males. This estimate of the marital premium is consistent with the previous estimates reported in Table 1, which typically range between 10% and 40%.¹⁵ However, accounting for familial ability greatly reduces the significance and the magnitude of the marital-status indicator variable – the coefficient estimate is basically reduced to zero, with correspondingly small t-values¹⁶. Furthermore, this result is robust to a correction for measurement error, and the original estimate of the correlation between ability and the married male indicator across families is positive and significant, reinforcing the conclusion that the significance of the marital-status indicator variable is subject to ability bias.

¹⁴The Hausman test statistics listed in Table 5 reject the hypothesis that similar estimates are generated by the OLS and Correlated Random Effects estimation procedures. Most of the difference in estimation results is due to a change in the marital status coefficient. There is also a strong change in the coefficient for the married female indicator, but this change is due to the reduced significance of being a married male. Regressions similar to those in Table 5 for a female sample show no significant changes in the marriage premium resulting from controlling for familial ability.

¹⁵See Korenman and Neumark (1991) or Loh (1996) for a survey of this literature.

¹⁶These results differ from those of Loh (1996), who does not find that familial controls significantly change the marital status coefficient for males.

These results provide a direct test of the competing theories for the significance of the marital premium for male workers: if the marriage institution itself improves the productivity of a married male, then controlling for ability should have no effect on this coefficient's estimate. Similarly, if it is the case that married males are the recipients of employer favoritism or if employers discriminate against non-married males, then the addition of ability controls also should not affect the significance of the married-male indicator variable. The marked decrease in the coefficient's point estimate and significance is evidence against both of these theories, suggesting that a selection effect can account for this significance. Specifically, these results imply that married males are more productive than unmarried males for reasons that are independent of an institutional explanation; these males were more productive before they became married.

Another result that is apparent from Table 5 is that little of the effect of educational attainment, tenure and union coverage variables can be attributed to correlation with familial ability. The coefficient estimates for these variables remain virtually unchanged after the inclusion of familial ability controls, and all of estimates of the correlation between these variables and ability are statistically insignificant. However, some caveats must accompany these results. Some studies¹⁷ have established the importance of match quality between a worker and a firm to the return to tenure. To account for this dimension of the analysis, it can be assumed that each twin pair have roughly the same match quality at their jobs. The limitations to the analysis of the union variable are due to the large standard errors associated with this variable's coefficient. Greater precision would be necessary before a proper assessment could be made of the effects of familial controls on this variable.

The results in Table 6 provide estimates of an earnings equations that includes an indicator variable for whether or not a worker uses a computer at his or her job. The introduction of this variable into the regression does not significantly change any of the results found in Table 5. And like the change in the marital-status indicator variable seen in Table 5, the strong significance of the computer-at-work variable under the OLS estimation procedure in the first column of table 6 is not evident once inter-twin ability

¹⁷See especially Abraham and Farber (1987).

controls are introduced into the analysis. Both the fixed-effect and correlated random effects estimation procedures yield estimates of this variable that are not only significantly different from those calculated without controls for ability, but also results that are not themselves statistically significant. These results are also robust to a measurement error correction¹⁸, which lends support to the argument that computers in the workplace do not themselves create a wage premium for a given worker; instead, the results indicate that more able workers tend to work at jobs which require the use of a computer.

5 Conclusion

The purpose of this paper was to use a simple econometric model on a data set of identical twins to control for familial ability and to determine its effect on estimates derived from typical earnings equations. Using this framework, it was established that the returns to union coverage, education and tenure were not really affected by familial ability controls. However, two other parameters were strongly affected by incorporating familial controls. First, not only was the coefficient of the marital-status indicator variable significantly different after controls for familial ability were introduced into the regression, it also became statistically insignificant as a result of the inclusion of these controls. Unlike institutional explanations offered to account for the significance of this variable in an earnings equation, such as a theory that relies upon the institution of marriage itself (Becker, 1973, 1981; Greenhalgh, 1980; Kenny, 1983; Korenman and Neumark, 1991; Loh 1996) or preferential treatment given to married men by employers (Hill, 1979; Bartlett and Callahan, 1984), this finding suggests that married males are always more productive than their unmarried counterparts. The inclusion of familial controls had a similarly dramatic effect on the return to using a computer at work, notably reducing the point estimate and significance of this coefficient. And, as

¹⁸This correction assumes that the variance of the measurement error evident in the computer-at-work indicator variable is equal to 0.02. For completeness, the correction was re-estimated with error variances of 0.04, 0.06, 0.08 and 0.1 for this indicator variable, and the results are generally similar. Even with a measurement error variance of 0.1 for the computer-at-work variable, the Hausmann statistic is still significant at the 5% level of significance. The difference between the fixed-effect and OLS estimates of the computer premium is significant only when the measurement error variance is between 0.2 and 0.8.

with the married-male indicator, this result suggests that the significance of the return to using a computer at work is not derived from the increased productivity caused by the computer itself (as suggested by Boozer, Krueger and Wolkon, 1992; Krueger, 1993; Autor, Katz and Krueger, 1998); instead, this suggests that workers who use computers at work were already more productive than their counterparts.

6 Appendix 1

Measurement error biases the estimated standard errors of the regression coefficients. To correct for this bias, the following formula must be used:

$$\tilde{V}(\tilde{b}_{OLS}) = \left(\frac{1}{n}\right) \tilde{\Omega}_1^{-1} [(n^{-1} X_j' X_j) * e_j' e_j + n^{-2} X_j' e_j e_j' X_j] \tilde{\Omega}_1^{-1}$$

$$\tilde{V}(\tilde{b}_{CRE}) = \left(\frac{1}{n}\right) \tilde{\Omega}_1^{-1} [(n^{-1} X_j' \Phi X_j) + \Sigma \beta \beta' \Sigma] \tilde{\Omega}_1^{-1}$$

$$\tilde{V}(\tilde{b}_{FE}) = \left(\frac{1}{n}\right) \tilde{\Omega}_2^{-1} [(n^{-1} \Delta X_j' \Delta X_j) * \Delta e_j' \Delta e_j + n^{-2} \Delta X_j' \Delta e_j \Delta e_j' \Delta X_j] \tilde{\Omega}_2^{-1}$$

where:

$$\tilde{\Omega}_1^{-1} = n^{-1} X_j' X_j - \Sigma$$

$$e_j = y_j - X_j' \tilde{b}_{GLS}$$

$$\tilde{\Omega}_2^{-1} = n^{-1} \Delta X_j' \Delta X_j - 2\Sigma$$

$$\Delta e_j = \Delta y_j - \Delta X_j' \tilde{b}_{FE}$$

$$\Phi = E(\varepsilon \varepsilon') = E[(e - \beta U)(e - \beta U)']$$

7 Appendix 2

To calculate the measurement error of an indicator variable, the fraction $\frac{m}{N}$ was computed from tables such as 4a-4c, where m represents the total number of discrepancies between the matched samples, and N represents the total number of observations in the matched samples. As such, the following measurement error variances were used for marital status:

$$V(u_{married}|male) = \frac{82}{7,210} = 0.011 \text{ and } V(u_{married}|female) = \frac{119}{8,253} = 0.014$$

With these values, it is now possible to compute the measurement error variances for marital status and being a married female in the pooled CPS/Census sample:

$$\begin{aligned} V(u_{married}) &= V(u_{married}|male) * (proportion \text{ male}) + V(u_{married}|female) * (proportion \text{ female}) \\ &= 0.0128 \end{aligned}$$

To compute the measurement error variance for the a married-female indicator variable, let Σ_{female} denote the summation over the sample of females, n_{female} the number of females, Σ_{male} the summation over the sample of males and n the total sample size.

$$\begin{aligned} V(u_{married \text{ female}}) &= \frac{1}{n} \Sigma_i (u_{married \text{ female}} - 0)(u_{married \text{ female}} - 0) \\ &= \frac{1}{n} [\Sigma_{female} (u_{married \text{ female}}^2) + \Sigma_{male} (0)] \\ &= \left(\frac{n_{female}}{n} \right) V(u_{married}|female) \\ &= (0.59)(0.014) = 0.0083 \end{aligned}$$

Finally, to compute the covariance between the measurement error for each respondent's marital status

and the measurement error for being a married female, it's necessary to carry out the following calculation:

$$\begin{aligned}
cov(u_{married}, u_{married\ female}) &= \frac{1}{n} \sum_i (u_{married} - \bar{u}_{married})(u_{married\ female} - \bar{u}_{married\ female}) \\
&= \frac{1}{n} \sum_i (u_{married} - 0)(u_{married\ female} - 0) \\
&= \frac{1}{n} [\sum_{female} (u_{married\ female}^2) + \sum_{male} (0)] \\
&= \left(\frac{n_{female}}{n} \right) V(u_{married} | female) \\
&= 0.0083
\end{aligned}$$

The measurement error variance for unionization status can be estimated using cross-tabulations from Freeman's (1984) work with the matched "Dual Job" and "Pension" supplements of the Current Population Survey from May, 1979. Although, Freeman admits, there are differences in the timing of the questions in both surveys, he argues that these differences are sufficiently small as to give a "reasonable first-order approximation to random error in union status".¹⁹ Freeman's cross-tabulation of the responses from the two May 1979 supplements are presented in Table 4c, and the variance of measurement error for union status is (trivially) calculated below:

$$V(u_{union}) = \frac{593}{18,257} = 0.032$$

To obtain estimates of the reporting error for years of tenure, Duncan's and Hill's (1985) cross-tabulations of employee survey data and employer records collected from a large manufacturing firm are used. Their study relies upon questions patterned after the PSID, and although the Twins questionnaire patterns its questions after the CPS, the careful approach used by Duncan and Hill and their ability to eliminate virtually all misclassification error from the employer records makes their estimates attractive for the purpose of this study. They report that the ratio of the measurement error variance to the true variance for years of tenure is 0.011, and the variance of years of tenure is 78.76 (this is reasonably close to the variance of tenure in the identical twins sample, which is 72.1). Thus, if the true years of tenure are denoted as T^* , where

¹⁹Freeman (1984), p. 12.

$T = T^* + u_{tenure}$, then the variance of the response error on years of tenure, u_{tenure} , is:

$$(90.91)V(u_{tenure}) = V(T^*)$$

$$V(u_{tenure}) = 0.857$$

If it is assumed that the measurement errors are not correlated across variables or individuals, then these estimates of the measurement error variance can be used to derive the following variance-covariance matrix of measurement error for the male sample, female sample and pooled sample:

$$\begin{aligned}\Sigma_{men} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{union} \end{bmatrix} \begin{bmatrix} \eta_{education} & \eta_{tenure} & \eta_{married} & \eta_{union} \end{bmatrix} \right] = \begin{bmatrix} 0.31 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 \\ 0 & 0 & 0.011 & 0 \\ 0 & 0 & 0 & 0.032 \end{bmatrix} \\ \Sigma_{women} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{union} \end{bmatrix} \begin{bmatrix} \eta_{education} & \eta_{tenure} & \eta_{married} & \eta_{union} \end{bmatrix} \right] = \begin{bmatrix} 0.31 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 \\ 0 & 0 & 0.014 & 0 \\ 0 & 0 & 0 & 0.032 \end{bmatrix} \\ \Sigma_{pooled} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{married\ female} \\ \eta_{union} \end{bmatrix} \begin{bmatrix} \eta_{education} & \eta_{tenure} & \eta_{married} & \eta_{married\ female} & \eta_{union} \end{bmatrix} \right] \\ &= \begin{bmatrix} 0.31 & 0 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 & 0 \\ 0 & 0 & 0.013 & 0 & 0 \\ 0 & 0 & 0.0083 & 0.0083 & 0 \\ 0 & 0 & 0 & 0 & 0.032 \end{bmatrix}\end{aligned}$$

In this case, the measurement error matrices are:

$$\begin{aligned}\Sigma_{men} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{union} \\ \eta_{computer} \end{bmatrix} \begin{bmatrix} \eta_{ed} & \eta_{ten} & \eta_{marr} & \eta_{union} & \eta_{comp} \end{bmatrix} \right] \\ &= \begin{bmatrix} 0.31 & 0 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 & 0 \\ 0 & 0 & 0.011 & 0 & 0 \\ 0 & 0 & 0 & 0.032 & 0 \\ 0 & 0 & 0 & 0 & V(\eta_{comp}) \end{bmatrix} \\ \Sigma_{women} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{union} \\ \eta_{computer} \end{bmatrix} \begin{bmatrix} \eta_{ed} & \eta_{ten} & \eta_{marr} & \eta_{union} & \eta_{comp} \end{bmatrix} \right] \\ &= \begin{bmatrix} 0.31 & 0 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 & 0 \\ 0 & 0 & 0.014 & 0 & 0 \\ 0 & 0 & 0 & 0.032 & 0 \\ 0 & 0 & 0 & 0 & V(\eta_{comp}) \end{bmatrix} \\ \Sigma_{pooled} &= E \left[\begin{bmatrix} \eta_{education} \\ \eta_{tenure} \\ \eta_{married} \\ \eta_{married\ female} \\ \eta_{union} \\ \eta_{computer} \end{bmatrix} \begin{bmatrix} \eta_{ed} & \eta_{tenure} & \eta_{married} & \eta_{married\ female} & \eta_{union} & \eta_{computer} \end{bmatrix} \right] \\ &= \begin{bmatrix} 0.31 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.86 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.011 & 0 & 0 & 0 \\ 0 & 0 & 0.0083 & 0.0083 & 0 & 0 \\ 0 & 0 & 0 & 0.014 & 0.032 & 0 \\ 0 & 0 & 0 & 0 & 0 & V(\eta_{comp}) \end{bmatrix}\end{aligned}$$

where $V(\eta_{comp})$ ranges in value from 0.02 to 0.1.

References

- [1] Abraham, Katherine G. and Henry S. Farber. "Job Duration, Seniority and Earnings." *American Economic Review*, June 1987, 77(3), pp. 278-297.
- [2] Altonji, Joseph G. and Robert A. Shakotko. "Do Wages Rise with Job Seniority?" *Review of Economic Studies*, July 1987, 54(3), pp. 437-459.
- [3] Angrist, Joshua D. and Alan B. Krueger. "Empirical Strategies in Labor Economics." in *Handbook of Labor Economics, Volume 3A*. Edited by Orley Ashenfelter and David Card, pp. 1277-1366. New York, NY: Elsevier, 1999.
- [4] Ashenfelter, Orley, Colm Harmon and Hessel Oosterbeek. "A Review of Estimates of the Schooling/earnings Relationship, with Tests for Publication Bias." *Labour Economics*, 6 (1999), pp.453-470.
- [5] Ashenfelter, Orley and Alan Krueger. "Estimates of the Economic Return to Schooling from a new Sample of Twins." *American Economic Review*, December 1994, 84(5), pp. 1157-1173.
- [6] Ashenfelter, Orley and Cecilia Rouse. "Income, Schooling and Ability: Evidence from a New Sample of Twins." *Quarterly Journal of Economics*, February 1998, 113(1), pp. 253-284.
- [7] Ashenfelter, Orley and David Zimmerman. "Estimates of the Return to Schooling with Data on Fathers, Sons and Brothers." *Review of Economics and Statistics*, February 1997, 79(1), pp. 1-9.
- [8] Autor, David; Lawrence F. Katz and Alan B. Krueger. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, November 1998, pp. 1169-1213.
- [9] Bartlett, Robin L. and Charles Callahan, III. "Wage Determination and Marital Status: Another Look." *Industrial Relations*, Winter 1984, 23(1), pp. 90-96.
- [10] Becker, Gary S. "A Theory of Marriage: Part I." *Journal of Political Economy*, July-August 1973, 81(4), pp.813-846.

- [11] Becker, Gary S. *A Treatise on the Family*. Cambridge: Harvard University Press. 1981.
- [12] Ben-Porath, Yoram. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy*, August 1967, 75(4), pp. 352-365.
- [13] Boozer, Michael A.; Alan B. Krueger and Shari Wolkon. "Race and School Quality Since Brown v. Board of Education." *Brookings Papers on Microeconomics*, 1992, 0(0), pp. 269-326.
- [14] Bound, John and David A. Jaeger. "Do Compulsory School Attendance Laws Alone Explain the Association between Quarter of Birth and Earnings?" Forthcoming in *Research in Labor Economics*.
- [15] Bound, John; David A. Jaeger and Regina M. Baker. "Problems With Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Variable is Weak." *Journal of the American Statistical Association*, June 1995, 90(430), pp. 443-450.
- [16] Bound, John and Gary Solon. "Double Trouble: On the Value of Twins-Based Estimation of the Return to Schooling." *Economics of Education Review*, April 1999, 18(2), pp. 169-182.
- [17] Bronars, Stephen G. and Melissa Famulari. "Wage, Tenure and Wage Growth Variation Within and Across Establishments." *Journal of Labor Economics*, April 1997, 15(2), pp. 285-317.
- [18] Card, David. "The Causal Effect of Education on Earnings." in *Handbook of Labor Economics, Volume 3A*. Edited by Orley Ashenfelter and David Card, pp. 1801-1863.
- [19] Card, David. "The Effect of Unions on the Structure of Wages: A Longitudinal Analysis." *Econometrica*, July 1996, 64(4), pp. 957-979.
- [20] Chamberlain, Gary. "Multivariate Regression Models for Panel Data." *Journal of Econometrics*, January 1982, 18(1), pp. 5-46.
- [21] Cornwell, Christopher and Peter Rupert. "Unobservable Individual Effects, Marriage and the Earnings of Young Men." *Economic Inquiry*, April 1997, 35(2), pp. 285-294.

- [22] Deaton, Angus. "Panel Data From Time Series of Cross-Sections." *Journal of Econometrics*, October-November 1985, 30(1-2), pp. 109-126.
- [23] DiNardo, John E. and Jorn-Steffen Pischke. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure, too?" *Quarterly Journal of Economics*, February 1997, 113(1), pp. 291-303.
- [24] Duncan, Greg J. and Daniel H. Hill. "An Investigation of the Extent and Consequences of Measurement Error in Labor-Economic Survey Data." *Journal of Labor Economics*, October 1985, 3(4), pp.508-532.
- [25] Fuller, Wayne A. "Regression Analysis for Sample Survey." *Sankhya: The Indian Journal of Statistics*, 1975, C37, pp. 117-132.
- [26] Freeman, Richard B. "Longitudinal Analyses of the Effects of Trade Unions." *Journal of Labor Economics*, January 1984, 2(1), PP.1-26.
- [27] Goldin, Claudia and Solomon Polachek. "Residual Differences by Sex: Perspectives on the Gender Gap in Earnings." *American Economic Review*, May 1987, 77(2), pp. 143-151.
- [28] Greenhalgh, Christine A. "Male-Female Wage Differentials in Great Britain: Is Marriage an Equal Opportunity?" *Economic Journal*, December 1980, 90(363), pp.751-775.
- [29] Griliches, Zvi. "Notes on the Role of Education in Production Functions and Growth Accounting." in: W.L. Hansen, ed., *Education, Income and Human Capital: Studies in Income and Wealth 35*. New York: Columbia University Press for the National Bureau of Economic Research.
- [30] Griliches, Zvi. "Estimating the Returns to Schooling: Some Econometric Problems." *Econometrica*, January 1977, 45(1), pp. 1-22.
- [31] Griliches, Zvi. "Sibling Models and Data in Economics: Beginnings of a Survey." *Journal of Political Economy*, October 1979, 87(5), Part 2, pp. S37-S64.

- [32] Gronau, Reuben. “Sex-Related Wage Differentials and Women’s Interrupted Labor Careers – the Chicken or the Egg?” *Journal of Labor Economics*, July 1988, 6(3), pp. 277-301.
- [33] Hausman, Jerry A. “Specification Tests in Econometrics.” *Econometrica*, November 1978, 46(6), pp. 1251-1271.
- [34] Hausman, Jerry A and William E. Taylor. “Panel Data and Unobservable Individual Effects.” *Econometrica*, November 1981, 49(6), pp. 1377-1398.
- [35] Hill, Martha. “The Wage Effects of Marital Status and Children.” *Journal of Human Resources*, Fall 1979, 14(4), pp. 579-593.
- [36] Kenny, Lawrence W. “The Accumulation of Human Capital During Marriage by Males.” *Economic Inquiry*, April 1983, 21(2), pp. 223-231.
- [37] Korenman, Sanders and David Neumark. “Marriage, Motherhood and Wages.” *Journal of Human Resources*, Spring 1992, 27(2), pp. 233-255.
- [38] Korenman, Sanders and David Neumark. “Does Marriage Really make Men More Productive?” *Journal of Human Resources*, Spring 1991, 26(2), pp. 282-307.
- [39] Krueger, Alan B. “How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989.” *Quarterly Journal of Economics*, February 1993, 108(1), pp. 33-60.
- [40] Loh, Eng Seng. “Productivity Differences and the Marriage Wage Premium for White Males.” *Journal of Human Resources*, Summer 1996, 31(3), pp. 566-588.
- [41] Lynch, Lisa M. “Private Sector Training and the Earnings of Young Workers.” *American Economic Review*, March 1992, 82(1), pp. 299-312.
- [42] Mincer, Jacob. “Investment in Human Capital and Personal Income Distribution.” *Journal of Political Economy*, August 1958, 66(4), pp. 281-302.

- [43] Moffitt, Robert. "Profiles of Fertility, Labour Supply and Wages of Married Women: A Complete Life-Cycle Model." *Review of Economic Studies*, April 1984, pp. 263-278.
- [44] Nakosteen, Robert A. and Michael A. Zimmer. "Marital Status and Earnings of Young Men: A Model with Endogenous Selection." *Journal of Human Resources*, Spring 1987, 22(2), pp. 248-268.
- [45] Neumark, David and Michele McLennan. "Sex Discrimination and Women's Labor Market Outcomes." *Journal of Human Resources*, Fall 1995, 30(4), pp. 713-740.
- [46] Neumark, David and Sanders Korenman. "Sources of Bias in Women's Wage Equations: Results Using Sibling Data." *Journal of Human Resources*, Spring 1994, 29(2), pp. 379-405.
- [47] Neumark, David. "Biases in Twin Estimates of the Return to Schooling." *Economics of Education Review*, April 1999, 18(2), pp. 143-148.
- [48] Parent, Daniel. "Industry-Specific Capital and the Wage Profile: Evidence from the NLSY and the PSID." *Princeton University, Industrial Relations Section, Working Paper #350*, November 1995.
- [49] Pencavel, John. "The Market Work Behavior and Wages of Women." *Journal of Human Resources*, Fall 1998, 33(4), pp. 771-804.
- [50] Siebert, W.S. and P.J. Sloane. "The Measurement of Sex and Marital Status Discrimination at the Workplace." *Economica*, May 1981, 48(190), pp. 125-141.
- [51] Topel, Robert. "Specific Capital, Mobility and Wages: Wages Rise with Job Seniority." *Journal of Political Economy*, February 1991, 99(1), pp. 145-176.
- [52] United States Bureau of the Census, Evaluation and Research Program. "Accuracy of Data for Selected Population Characteristics as Measured by the 1970 CPS-Census Match." U.S. Government Printing Office, 1975.
- [53] Zellner, Arnold. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association*, June 1962, 57(298), pp. 348-368.

**Table 1: A Review of the Results from Studies Examining the Causal Effect of
Different Regressors**

Regressor		Estimated Effect on Log Wages
Education	Angrist and Krueger (1991a)	6-8%
	Card (1993)	13%
	Ashenfelter and Rouse (1998)	10-12%
	Bound, Jaeger and Baker (1995)	6%
Tenure	Topel (1991)	5.5%
	Bronars and Famulari (1997)	1.2%
	Abraham and Farber (1987)	0.25-0.5%
	Altonji and Shakotko (1987)	0.6-1.0%
Marital Status (for males)	Hill (1979)	26-31%
	Bartlett and Callahan (1984)	20-32%
	Korenman and Neumark (1991)	15-18%
	Nakosteen and Zimmer (1987)	35-41%
	Cornwell and Rupert (1997)	5-7%
Computer Use at Work	Krueger (1993)	10-15%
	Boozer, Krueger and Wolkon (1992)	22-23%
	DiNardo and Pischke (1997)	Negligible

Table 2: Means and Standard Deviations of the CPS and Twins Data

	Identical Twins	1993 April CPS	1993 October CPS
Self-Reported Education	14.06 (2.07)	13.41 (2.41)	13.41 (2.46)
Hourly Wage	14.39 (12.21)	13.23 (8.37)	12.17 (7.53)
Age	37.56 (10.92)	38.89 (11.11)	37.74 (11.34)
Female	0.59 (0.49)	0.47 (0.50)	0.48 (0.50)
Covered by union	0.21 (0.40)	0.21 (0.40)	0.17 (0.38)
Job tenure (years)	8.36 (8.49)	8.60 (7.76)	
Married	0.49 (0.50)	0.66 (0.47)	0.63 (0.48)
Computer used at work ¹	0.59 (0.48)		0.49 (0.50)
Sample Size	778	17,132	11,384

¹ The Computer at Work mean and standard deviation are based on only 606 observations in the Twins sample, because questions about this variable were asked in only three of the four sampling years (1992, 1993 and 1995)

Table 3: OLS estimates of the Earnings Equation
Using the CPS and Identical Twins Data sets

	Identical Twins	1993 April CPS	Identical Twins	1993 October CPS
Own education	0.114 (0.009)	0.092 (0.002)	0.095 (0.010)	0.071 (0.002)
Age	0.081 (0.011)	0.056 (0.002)	0.074 (0.012)	0.061 (0.002)
Age ² (/100)	-0.094 (0.013)	-0.064 (0.003)	-0.075 (0.015)	-0.063 (0.003)
Tenure	0.022 (0.003)	0.015 (0.0006)		
Female	-0.147 (0.048)	-0.147 (0.011)	-0.231 (0.055)	-0.190 (0.014)
Married	0.231 (0.058)	0.121 (0.013)	0.270 (0.064)	0.139 (0.013)
Married Female	-0.248 (0.072)	-0.132 (0.017)	-0.280 (0.080)	-0.143 (0.017)
Covered by a union	0.068 (0.044)	0.103 (0.009)	0.150 (0.049)	0.187 (0.011)
Computer Use at Work			0.239 (0.041)	0.233 (0.009)
Sample Size	778	15,301	606	11,384
R ²	0.408	0.390	0.412	0.398

Standard errors are reported in parentheses below the point estimate of the coefficient.

**Table 4: The Matrix of Measurement Error Variances
and Covariances for the Regressors**

	$\eta_{\text{education}}$	η_{tenure}	η_{married}	$\eta_{\text{married female}}$	η_{union}	η_{computer}
$\eta_{\text{education}}$	0.31	0	0	0	0	0
η_{tenure}	0	0.86	0	0	0	0
η_{married}	0	0	0.013	0.0083	0	0
$\eta_{\text{married female}}$	0	0	0.0083	0.014	0	0
η_{union}	0	0	0	0	0.032	0
η_{computer}	0	0	0	0	0	$V(\eta_{\text{comp}})$

$V(\eta_{\text{comp}})$ ranges in value from 0.02 to 0.1.

**Table 4a: Misclassification error for Marital Status for Men
in the CPS and Census Records**

CPS Classification	Census Classification		Total
	Married	Not Married	
Married	5,103	41	5,144
Not Married	41	2,025	2,066
Total	5,144	2,066	7,210

**Table 4b: Misclassification error for Marital Status for Women
in the CPS and Census Records**

CPS Classification	Census Classification		Total
	Married	Not Married	
Married	5,214	58	5,272
Not Married	61	2,920	2,981
Total	5,275	2,978	8,253

**Table 4c: Misclassification error for Unionization Status
in the May 1979 CPS Records**

Covered by CBA on the CPS Dual Job Supplement	Covered by Collective Bargaining Agreement on the CPS Pension Supplement		Total
	Yes	No	
Yes	3,976	272	4,248
No	321	13,688	14,009
Total	4,297	13,950	18,257

**Table 5: OLS, Correlated Random Effects and Fixed-Effects Earnings Equation
Estimates: Both With and Without a Measurement-Error Correction**

	Corrected for Measurement Error			Uncorrected for Measurement Error		
	OLS	CRE	Fixed-Effects	OLS	CRE	Fixed-Effects
Own Education	0.124 (0.011)	0.143 (0.030)	0.143 (0.028)	0.114 (0.009)	0.092 (0.017)	0.092 (0.017)
Avg. Education		-0.023 (0.033)			0.025 (0.020)	
Age	0.080 (0.011)	0.081 (0.013)		0.081 (0.011)	0.082 (0.013)	
Age Squared/100	-0.093 (0.013)	-0.096 (0.016)		-0.094 (0.013)	-0.096 (0.016)	
Married	0.244 (0.062)	0.053 (0.091)	0.053 (0.087)	0.231 (0.058)	0.061 (0.077)	0.061 (0.077)
Avg. Marital Status		0.256 (0.125)			0.236 (0.114)	
Married Female	-0.251 (0.077)	0.015 (0.119)	0.015 (0.115)	-0.248 (0.072)	-0.008 (0.101)	-0.008 (0.101)
Avg. Married Female		-0.352 (0.158)			-0.322 (0.144)	
Female	-0.137 (0.050)	-0.101 (0.065)		-0.147 (0.048)	-0.108 (0.064)	
Covered by a Union	0.090 (0.057)	0.117 (0.075)	0.117 (0.075)	0.068 (0.044)	0.083 (0.052)	0.083 (0.052)
Avg. Union		-0.046 (0.108)			-0.026 (0.085)	
Tenure	0.022 (0.003)	0.021 (0.003)	0.021 (0.003)	0.022 (0.003)	0.020 (0.003)	0.020 (0.003)
Avg. Tenure		0.003 (0.005)			0.003 (0.005)	
R ²	0.4356	0.4398	0.1913	0.4082	0.4128	0.1546
Hausman Statistic		11.39, p-value=0.044			17.39, p-value=0.0038	

Standard Errors are listed in parentheses.

**Table 6: OLS, Correlated Random Effects and Fixed-Effects Earnings Equation
Estimates: Both With and Without a Measurement-Error Correction**

	Corrected for Measurement Error			Uncorrected for Measurement Error		
	OLS	OLS with Family Effects	Fixed-Effects	OLS	OLS with Family Effects	Fixed-Effects
Own Education	0.114 (0.011)	0.136 (0.043)	0.133 (0.036)	0.105 (0.010)	0.078 (0.020)	0.078 (0.020)
Avg. Education		-0.028 (0.046)			0.027 (0.024)	
Age	0.071 (0.012)	0.066 (0.014)		0.073 (0.012)	0.068 (0.014)	
Age Squared/100	-0.081 (0.015)	-0.077 (0.018)		-0.084 (0.014)	-0.079 (0.018)	
Married	0.254 (0.066)	0.00003 (0.096)	0.0004 (0.094)	0.241 (0.061)	0.008 (0.084)	0.008 (0.084)
Avg. Marital Status		0.350 (0.131)			0.329 (0.121)	
Married Female	-0.238 (0.084)	0.017 (0.132)	0.016 (0.131)	-0.233 (0.078)	0.006 (0.114)	0.007 (0.114)
Avg. Married Female		-0.338 (0.170)			-0.321 (0.157)	
Female	-0.181 (0.056)	-0.160 (0.071)		-0.191 (0.054)	-0.165 (0.070)	
Covered by a Union	0.133 (0.062)	0.121 (0.084)	0.122 (0.085)	0.100 (0.047)	0.098 (0.058)	0.098 (0.058)
Avg. Union		0.016 (0.120)			0.011 (0.093)	
Tenure	0.019 (0.003)	0.017 (0.004)	0.017 (0.004)	0.019 (0.003)	0.016 (0.003)	0.016 (0.003)
Avg. Tenure		0.002 (0.006)			0.003 (0.005)	
Computer at Work	0.215 (0.046)	0.068 (0.058)	0.069 (0.057)	0.205 (0.040)	0.075 (0.048)	0.075 (0.048)
Avg. Computer		0.229 (0.089)			0.205 (0.078)	
R ²	0.4820	0.4966	0.1659	0.4537	0.4676	0.1370
Hausman Statistic		31.56, p-value<0.0001			47.21, p-value<0.0001	

Standard Errors are listed in parentheses.