



**CEP Discussion Paper No 1163**

**September 2012**

**A Cautionary Note on Using Industry  
Affiliation to Predict Income**

**Jörn-Steffen Pischke and Hannes Schwandt**

## **Abstract**

Many literatures investigate the causal impact of income on economic outcomes, for example in the context of intergenerational transmission or well-being and health. Some studies have proposed to use employer wage differentials and in particular industry affiliation as an instrument for income. We demonstrate that industry affiliation is correlated with fixed individual characteristics, specifically parents' education and own height, conditional on the covariates typically controlled for in these studies. These results suggest that there is selection into industries based on unobservables. As a result the exclusion restriction in many IV studies of this type is likely violated.

Keywords: industry wage differentials, health, happiness, intergenerational mobility

JEL Classifications: D31, I14, I3, J31

This paper was produced as part of the Centre's Labour Markets Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

## **Acknowledgements**

We thank Georg Graetz for excellent research assistance and the Centre for Economic Performance at the LSE for supporting this research.

Jörn-Steffen Pischke is an Associate of the Labour Markets Programme at the Centre for Economic Performance and Professor of Economics, London School of Economics and Political Science. Hannes Schwandt is a Visiting Research Scholar, Center for Health and Wellbeing, Woodrow Wilson School, Princeton University.

Published by  
Centre for Economic Performance  
London School of Economics and Political Science  
Houghton Street  
London WC2A 2AE

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system or transmitted in any form or by any means without the prior permission in writing of the publisher nor be issued to the public or circulated in any form other than that in which it is published.

Requests for permission to reproduce any article or part of the Working Paper should be sent to the editor at the above address.

© J-S. Pischke and H. Schwandt , submitted 2012

# 1 Introduction

Many literatures ask about the causal impact of income on a variety of economic outcomes. One example is intergenerational transmission; the question whether children of richer parents fare better in terms of their own economic performance (Solon, 1999). Another example is the health-income gradient: higher income individuals tend to be healthier. Is this association causal, do richer individuals differ in other dimensions, or does the causality run the opposite way (Cutler, Lleras-Muney, Vogl, 2011)? Furthermore, income is an important correlate in happiness regressions relating individual life satisfaction to various economic determinants (Blanchflower and Oswald, 2004). Does higher income cause happiness?

Sorting out causality in these and other applications is difficult. A number of studies in the literature have used employer wage differentials and particularly industry affiliation as an instrumental variable for individual or family income. Examples of such studies are Shea (2000) who uses industry affiliation, union membership, and job loss as instruments for parents' income in order to learn about intergenerational transmission. Luttmer (2005) uses interactions of industry and occupation as instruments for income in happiness regressions, an avenue also followed by Luechinger (2009). This idea has been extended by Pischke (2011), who focuses on industry differentials only, and has also been used by Li et al. (2011).

Industry wage differentials in particular are large and remain after controlling for many covariates including individual fixed effects (Krueger and Summers, 1988; Gibbons and Katz, 1992) and ability test scores (Blackburn and Neumark, 1992). As a result, researchers using these wage differentials as instruments for income may have a reasonable claim of identifying causal effects of income not contaminated by unobserved personal attributes and selection. In this note we provide some evidence to caution against this optimism. Following the same specifications as in Pischke (2011) we show

that industry differentials correlate with mother’s education and own height. Both of these variables are pre-determined by the time industry affiliation is measured, and should therefore not be affected by industry choice.

The statistical association with industry wage effects which we find therefore suggests selection in industry choice which correlates with personal characteristics related to parental background and height. These characteristics might, for example, be unmeasured cognitive or non-cognitive skills or personality traits. We conclude by discussing why we think the types of variables we use, mother’s education and height, might be useful as specification checks but offer little hope in improving inference in regression or IV frameworks. We conjecture that this remains true for even for better measures of the underlying omitted skills or traits, like ability test scores.

## 2 Data

In order to study the effect of parental education we use data from the 1972 to 2006 waves of the US General Social Survey (GSS). The GSS is a repeated cross-sectional survey, carried out every one to two years. The GSS is also the main dataset analyzed in Pischke (2011) and we use the same sample restrictions. The primary sample consists of employed men aged 20 – 64 without missing values for any of the covariates used in the analysis.

Our outcome measures of primary interest are happiness and parental education. Happiness is transformed as explained in Pischke (2011), so that all results can be interpreted in terms of standard deviation units. As main parental education variable we use the highest year of completed schooling of the respondent’s mother. We exclude missing values and those individuals reporting zero years of education. We focus on mother’s education because there are fewer missing values in mother’s education than in father’s education. Using father’s education or combining the education of both parents yields comparable results.

Family income, our main regressor, is a bracketed variable and we assign midpoints as described in Pischke (2011). Industry and occupation affiliation of the respondent are aggregated into 32 and 22 categories, respectively. Details are given in the appendix.

The wives sample consists of married females aged 20 to 64 with employed husbands. The industry and occupation variables used in this sample refer to the husbands, while other controls refer to the respondent.

In order to corroborate our results on parental education from the GSS we also present results on body height using the US National Health Interview Survey (NHIS). The NHIS is also a repeated cross-section carried out every year with about 30,000 to 50,000 respondents per wave. We use waves from 1974 to 2009 and restrict the sample to employed men aged 20-64.

Our outcome measures of primary interest in the NHIS are self-reported health and self-reported body height. Self-reported health is the answer to the question “Would you say your health in general is excellent, very good, fair, or poor?” We transform this health measure the same way as happiness in the GSS such that results can be interpreted in terms of standard deviations. Body height is measured in centimeters.

We group industry and occupation affiliations of the respondent into 28 and 18 categories, respectively. These groups are relatively commensurate with the GSS classifications, although a precise correspondence is not possible. Details are in the appendix.

### **3 Results**

Table 1 displays regressions of happiness on the logarithm of family income for the sample of men from the GSS. Each column shows results for a different set of included controls. The specifications in each column are estimated by OLS, 2SLS and using Akerberg and Devereux’s (2009) Improved Jackknifed IV estimator (IJIVE). In the first four columns we reestimate the baseline

specifications from Pischke (2011) in the sample without missing values for mother's education. In columns (5) to (8) we repeat these regressions including mother's education as an additional control.

The OLS specifications in the first row indicate a positive and significant association of family income with happiness that is robust to the inclusion of a broad set of control variables. Using industry affiliation as instrument for family income results in somewhat higher and less precisely estimated coefficients. The coefficients in the first four columns are very similar to the estimates in Pischke (2011) although the IV results are slightly higher.

In columns (5) to (8) we repeat the baseline regressions including the years of education of the respondent's mother as additional control variable. Maternal education is an important component of a respondent's family background. If there is strong selection into industries due to unobservables related to a respondent's family background then the inclusion of mother's education should substantially change our IV estimates. This is not the case: coefficient estimates are virtually identical to those in the earlier columns. These results might suggest that omitted variable bias due to unobserved heterogeneity in family background is not particularly important. In other words, selection into industries based on family background does not seem to be a major issue.

But this is not the end of the story. In Table 2 we look at this potential selection issue from a different angle. Instead of including mother's education as a control we use this proxy for family background as dependent variable. The first four columns display the baseline results from the previous table. In columns (5) to (8) we repeat these regressions using as dependent variable mother's education instead of the respondent's happiness. In columns (5) and (6) the pattern of results is remarkably similar to those for happiness. There is a strong correlation between income and mother's education. IV estimates are larger than OLS estimates. It is difficult to think of these results as causal effects: income differences due to industry affiliation should not affect

predetermined parental education. So the obvious conclusion to draw is that these estimates reflect selection bias. Estimates are lower in columns (7) and (8) where we include occupation dummies as controls. But standard errors are large so that this is probably just due to sampling variation as we don't find a similar pattern in the NHIS data described below.

In Table 3 we turn to results for married women. Pischke (2011) uses this group as a specification check. If the correlations between industry income differentials and happiness are due to selection we should see less of an association between husbands industry affiliation and wife's happiness. In particular, for working wives we can control for the woman's own industry, which should be a reasonable guard against selection effects. In the sample we analyze here the IV estimates for income in the regressions using happiness for working wives are a lot lower than those for men. This is not the case in the original sample used in Pischke (2011) where the results for working wives differed little from those for the husbands. In any case, there is no evidence in either sample that controlling for wives' own industry affiliation (which should take care of any selection) lowers the coefficient on income.

Turning to the results using mother's education as dependent variable we find much more consistent results across specifications. The IV results are generally large and well above the OLS results. Controlling for wives' own industry does nothing to the results. Pischke (2011) took this type of evidence as support for the causal interpretation of the results on happiness. Our results for mother's education cast doubt on the usefulness of the wives sample as a specification check since a causal interpretation does not make sense for this dependent variable.

Using the same sample, in Table 4 we turn to the type of instrument set used in Luttmer (2005) combining both industry affiliation and occupation. We find that mother's education is even more strongly related to occupation than industry wage differentials. This suggests that neither variable is useful in order to generate exogenous variation in income.

In Table 5 we explore other employer characteristics as instruments, including union status used in Shea (2001). Our inference here is hindered by the fact that the IV results for mother’s education are very imprecisely estimated. The point estimates using union status and firm size are negative and numerically large but not statistically significant. As a result, we can say relatively little about these employer attributes from the small GSS samples.

In order to corroborate our findings further we turn to data from the NHIS to look at health as an outcome. While health is an important outcome in its own right another advantage of the NHIS is the much larger sample sizes compared to the GSS. Unfortunately, the NHIS offers less employment related information. So we return to industry affiliation as the instrument here. We check the health results using height as an alternative outcome which should not be affected by industry affiliation. Body height is largely fixed by age 20 (Hamill, 1977).

Columns (1) to (3) of Table 6 reveal IV coefficients slightly below the OLS results. Taken at face value, these results suggest that a sizeable portion of the association between health and income is due to a causal effect running from income to health with something of an upward bias to the OLS results. However, as with our findings for mother’s education, the results for height shed doubt on this interpretation. The association between income and height becomes stronger in the IV estimates cautioning against interpreting these results causally. The results in this larger sample are more precisely estimated than those from the GSS, and they are very stable independently of what controls are included.

In Table 6 we use a sample of men aged 20 – 64, similar to the sample from the GSS used for tables 1 and 2. One caveat with this age group is that older men tend to shrink slightly, and this may be related to income. To guard against this we also present results for men aged 20 – 29 in Table 7, an age group for whom this should not be a concern. The large sample sizes in the NHIS easily facilitate such cuts of the data. The results are qualitatively

very similar to those in Table 6, so differential shrinkage does not seem to be a factor in our findings.

## 4 Interpretation

Our results mirror earlier findings by Blackburn and Neumark (1992) regarding the association of industry wage differentials and ability measures. These authors found that ability measures like IQ type test scores are strongly correlated with industry wage differentials. On the other hand, controlling for the test scores hardly alters estimated industry effects in a wage regression. We find the same pattern of results for mother’s education and height. How do these results make sense, and what do they tell us about various empirical strategies to uncover causal effects in the type of applications we have discussed, which use income as a (potentially endogenous) regressor?

We discuss these issues in the following statistical framework. Consider the regression equation

$$h_i = \beta y_i + \gamma x_i + \varepsilon_i \tag{1}$$

where  $h_i$  is an outcome like health, happiness, or children’s income,  $y_i$  is own income,  $x_i$  is a confounder, and  $\varepsilon_i$  is a regression residual, orthogonal to  $y_i$  and  $x_i$ . Conditional on the confounder  $x_i$  the regression coefficient  $\beta$  is the causal effect of income on  $h_i$ .  $x_i$  may correspond to difficult to observe attributes like ability, personal traits, etc. We will also assume that conditional on the confounder  $x_i$  industry affiliation is random. Hence, we can interpret our IV results as replacing income  $y_i$  in (1) by its prediction using industry wage effects.

Income is related to the confounder by the regression equation

$$y_i = \delta x_i + v_i. \tag{2}$$

The confounder  $x_i$  is not directly observed. Instead, we observe a proxy

correlated with  $x_i$  characterized by the regression

$$m_i = \lambda x_i + u_i \tag{3}$$

where  $m_i$  might be mother's education or own height. We assume  $cov(v_i, u_i) = 0$ , i.e. only  $x_i$  links income with the measure  $m_i$ .

Here, we give some intuition for our results within this framework. We derive the relevant implications formally in the appendix. Our regression results indicate that income matters for mother's education (or height) both in the OLS and IV regressions (Table 2, cols. (5) to (8)). This implies both  $\lambda$  and  $\delta$  have to be positive, since  $x_i$  is the only link between these two variables.

Our next finding is that the estimated effect of income on the outcome  $h_i$  is basically the same whether we control for  $m_i$  in the regression or not (Table 1, cols (1) to (4) versus (5) to (8)). One explanation for the results is that the noise in the measure  $m_i$  is large (i.e.  $\sigma_u^2 \gg 0$ ). This noise is a classical measurement error and does not matter when  $m_i$  is on the left hand side, so the measure  $m_i$  is still useful to glean information on whether there is any bias in the OLS or IV regressions (from the  $m_i$  on  $y_i$  regression). But the noise leads to attenuation when using  $m_i$  on the right hand side of the regression, so it becomes essentially useless as a control in this case. This seems to make sense for measures like mother's education and particularly height, which clearly must be very crude variables to get at the true underlying confounder  $x_i$ . Variables like ability test scores should be better proxies for  $x_i$ , in the sense that  $\lambda$  is larger and/or  $\sigma_u^2$  smaller. However, the Blackburn and Neumark (1992) results indicate that even ability test scores exhibit pretty much the same features. As a result the available variables of this type seem to offer little mileage as controls in regression studies. Our insights here are not new; they are very much reminiscent of Griliches (1977) in his discussion of estimating the returns to schooling.

In order to interpret the IV results in this context think of replacing income with the part of income predicted by industry wage effects. For this

predicted income, the relative size of  $\delta$  and  $\sigma_v^2$  may be different compared to raw income (which is relevant for the OLS results). The IV results for happiness are above the OLS estimates, and this is true for the regression of mothers education as well. Within this particular framework this has to imply that  $\delta$  becomes more important relative to  $\sigma_v^2$  for predicted income. This implies that both the OLS and IV results are biased upwards but the IV results are biased even more.

Let us make this slightly more precise. In terms of our framework in eqs. (1) and (2) the variable  $v_i$  is a valid instrument for income. In other words, the variation in income due to a valid instrument needs to satisfy the condition  $\delta = 0$ . This motivates using the IV regression of  $m_i$  on  $y_i$  as a specification check. In practice, few instruments might satisfy the condition  $\delta = 0$  literally. Moreover, most instruments use little of the variation in the endogenous regressor. As a result, both  $\delta$  and  $\sigma_v^2$  will be lower in the IV case. We show in the appendix that IV is less biased than OLS whenever  $\delta / (\delta^2 + \sigma_v^2)$  is smaller for the income predicted by the instrument than for raw income.  $\delta$  may be very small for predicted income but this is of little comfort with relatively weak instruments, an insight which goes back to Bound, Jaeger and Baker (1995). These authors show that the relative bias of IV is related to the size of the partial  $R^2$  or  $F$ -statistic on the excluded instruments in the first stage. These metrics are not just important to assess small sample bias in two stage least squares regressions but also asymptotic bias due to small violations of the exclusion restrictions in the form of  $\delta \neq 0$ .

## 5 Conclusion

In this note we have assessed the usefulness of industry wage differentials as instruments in regression models for happiness or health with income as an endogenous regressor. Our conclusion is broadly negative: we do not believe that industry wage differentials offer a useful source of variation in income

to establish causal effects. This is based on OLS and IV regressions using fixed personal characteristics as left hand side variables in the respective regressions, which show large effects. One obvious, though hardly novel conclusion from our work is that a healthy degree of doubt about the use of instrumental variables is often warranted, even when the IV regressions pass some purported specification tests. Using fixed personal characteristics as dependent variable offers a useful specification check. We argue that this is the case even for variables which might be poorly measured and are of little value as control variables. Such variables should be available in many data sets.

## References

- [1] Akerberg, Daniel A., and Paul J. Devereux (2009) “Improved JIVE Estimators for Overidentified Linear Models with and without Heteroskedasticity,” *Review of Economics and Statistics*, 91, No. 2 (May), 351-362.
- [2] Blackburn, McKinley, and David Neumark (1992) “Unobserved Ability, Efficiency Wages, and Interindustry Wage Differentials,” *Quarterly Journal of Economics*, Vol. 107, No. 4 (Nov.), 1421-1436.
- [3] Blanchflower, David G. and Andrew J. Oswald (2004) “Well-being over time in Britain and the USA,” *Journal of Public Economics*, Volume 88, Issues 7–8, July , 1359–1386.
- [4] Bound, John, David A. Jaeger, and Regina M. Baker (1995) “Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak,” *Journal of the American Statistical Association*, Vol. 90, No. 430, June, 443-450.

- [5] Cutler, David M., Adriana Lleras-Muney, and Tom Vogl (2011). "Socioeconomic Status and Health: Dimensions and Mechanisms", in Sherry Glied and Peter Smith (eds.) *Oxford Handbook of Health Economics*, Oxford: Oxford University Press.
- [6] Gibbons, Robert and Lawrence F. Katz (1992) "Does Unmeasured Ability Explain Inter-Industry Wage Differentials?" *Review of Economic Studies*, 59, No. 3 (July), 515-535.
- [7] Griliches, Zvi (1977) "Estimating the Returns to Schooling - Some Econometric Problems," *Econometrica*, vol. 45, January, 1-22
- [8] Hamill, Peter V. V. (1977) "NCHS growth curves for children," Vital and health statistics: Series 11, Data from the National Health Survey; no. 165, Hyattsville, Md: National Center for Health Statistics.
- [9] Krueger, Alan B., and Lawrence H. Summers (1988) "Efficiency Wages and the Inter-Industry Wage Structure," *Econometrica*, Vol. 56, No. 2 (March), 259-293.
- [10] Li, Hongbin, Pak Wai Liu, Maoliang Ye, and Junsen Zhang (2011) "Does Money Buy Happiness? Evidence from Twins in Urban China," Working Paper, Tsinghua University (April).
- [11] Luechinger, Simon (2009) "Valuing Air Quality Using the Life Satisfaction Approach," *Economic Journal*, 119, No. 536 (March), 482-515.
- [12] Luttmer, Erzo F. P. (2005) "Neighbors as Negatives: Relative Earnings and Well-Being," *Quarterly Journal of Economics*, 120, No. 3 (August), 963-1002.
- [13] Pischke, Jörn-Steffen (2011) "Money and Happiness: Evidence from the Industry Wage Structure," NBER Working Paper 17056 (May).

- [14] Segal, Carmit (forthcoming) “Working When No One is Watching: Motivation, Test Scores, and Economic Success,” *Management Science*.
- [15] Shea, John (2000) “Does parents’ money matter?” *Journal of Public Economics*, 77, No. 2, (August), 155-184.
- [16] Solon, Gary (1999) “Intergenerational mobility in the labor market,” chapter 29 in: Orley Ashenfelter and David Card (eds.) *Handbook of Labor Economics*, vol. 3A, Amsterdam: Elsevier.

## 6 Appendix

The variables  $h_i$ ,  $y_i$ ,  $m_i$ , and  $x_i$  are defined by the regression equations

$$\begin{aligned} h_i &= \beta y_i + \gamma x_i + \varepsilon_i \\ y_i &= \delta x_i + v_i \\ m_i &= \lambda x_i + u_i. \end{aligned}$$

Normalize  $x_i$  so that  $\text{var}(x_i) = 1$ .

Consider the regression of  $y_i$  on  $m_i$

$$\begin{aligned} y_i &= \pi m_i + \tilde{y}_i \\ \pi &= \frac{\text{cov}(m_i, y_i)}{\text{var}(m_i)} = \frac{\text{cov}(\lambda x_i + u_i, \delta x_i + v_i)}{\lambda^2 + \sigma_u^2} \\ &= \frac{\lambda \delta}{\lambda^2 + \sigma_u^2} \end{aligned}$$

so that the residual of  $y_i$  after filtering out  $m_i$  is given by

$$\tilde{y}_i = y_i - \pi m_i = y_i - \frac{\lambda \delta}{\lambda^2 + \sigma_u^2} m_i.$$

The variances are

$$\begin{aligned} \text{var}(y_i) &= \delta^2 + \sigma_v^2 = \left( \frac{\lambda \delta}{\lambda^2 + \sigma_u^2} \right)^2 (\lambda^2 + \sigma_u^2) + \text{var}(\tilde{y}_i) \\ \text{var}(\tilde{y}_i) &= \delta^2 + \sigma_v^2 - \frac{\lambda^2 \delta^2}{\lambda^2 + \sigma_u^2} \\ &= \frac{(\lambda^2 + \sigma_u^2)(\delta^2 + \sigma_v^2) - \lambda^2 \delta^2}{\lambda^2 + \sigma_u^2} \\ &= \frac{\lambda^2 \sigma_v^2 + \sigma_u^2 (\delta^2 + \sigma_v^2)}{\lambda^2 + \sigma_u^2} \end{aligned}$$

Finally note that the regression coefficient of  $x_i$  on  $\tilde{y}_i$  is

$$\begin{aligned}
b_{x\tilde{y}} &= \frac{\text{cov}(x_i, \tilde{y}_i)}{\text{var}(\tilde{y}_i)} = \frac{\text{cov}\left(x_i, y_i - \frac{\lambda\delta}{\lambda^2 + \sigma_u^2} m_i\right)}{\text{var}(\tilde{y}_i)} \\
&= \frac{\text{cov}\left(x_i, \delta x_i + v_i - \frac{\lambda\delta}{\lambda^2 + \sigma_u^2} (\lambda x_i + u_i)\right)}{\text{var}(\tilde{y}_i)} \\
&= \frac{\delta - \frac{\lambda^2\delta}{\lambda^2 + \sigma_u^2}}{\text{var}(\tilde{y}_i)} = \frac{\delta(\lambda^2 + \sigma_u^2) - \lambda^2\delta}{\lambda^2\sigma_v^2 + \sigma_u^2(\delta^2 + \sigma_v^2)} \\
&= \frac{\delta\sigma_u^2}{\lambda^2\sigma_v^2 + \sigma_u^2(\delta^2 + \sigma_v^2)}.
\end{aligned}$$

Our primary interest is the regression

$$h_i = by_i + cm_i + e_i$$

and we get

$$\begin{aligned}
b &= \frac{\text{cov}(h_i, \tilde{y}_i)}{\text{var}(\tilde{y}_i)} = \frac{\text{cov}(\beta y_i + \gamma x_i + \varepsilon_i, \tilde{y}_i)}{\text{var}(\tilde{y}_i)} \\
&= \frac{\beta \text{var}(\tilde{y}_i) + \gamma \text{cov}(x_i, \tilde{y}_i)}{\text{var}(\tilde{y}_i)} \\
&= \beta + \gamma b_{x\tilde{y}} = \beta + \gamma \frac{\delta\sigma_u^2}{\lambda^2\sigma_v^2 + \sigma_u^2(\delta^2 + \sigma_v^2)}.
\end{aligned}$$

and running

$$\begin{aligned}
h_i &= b^* y_i + e_i^* \\
b^* &= \beta + \gamma b_{xy} = \beta + \gamma \frac{\text{cov}(x_i, y_i)}{\text{var}(y_i)} \\
&= \beta + \gamma \frac{\text{cov}(x_i, \delta x_i + v_i)}{\delta^2 + \sigma_v^2} \\
&= \beta + \gamma \frac{\delta}{\delta^2 + \sigma_v^2}
\end{aligned}$$

This corresponds to the regression coefficient we get from regressing  $h_i$  on  $y_i$  without controlling for  $m_i$ , i.e. the regressions in Tables 1 and 2, cols. (1) to (4).

Finally, consider the regression of  $m_i$  on  $y_i$ , corresponding to the regressions in columns (5) to (8) of Table 2:

$$\begin{aligned} m_i &= dy_i + e_i^m \\ d &= \frac{\text{cov}(m_i, y_i)}{\text{var}(y_i)} = \frac{\lambda\delta}{\delta^2 + \sigma_v^2}. \end{aligned}$$

This demonstrates the claim that  $d > 0$  implies  $\lambda > 0$  and  $\delta > 0$ .

In the OLS results we basically find  $b = b^*$  i.e. controlling for  $m_i$  hardly matters in the regression of  $h_i$  on  $y_i$  (Table 1, cols (1) to (4) versus (5) to (8)). If we make  $\sigma_u^2$  large we get

$$\lim_{\sigma_u^2 \rightarrow \infty} b_{x\tilde{y}} = \frac{\delta}{\delta^2 + \sigma_v^2} = b_{xy}.$$

On the other hand,  $\sigma_u^2$  does not figure in the expression for  $d$ , so poor measurement does not affect the regression of  $m_i$  on  $y_i$ .

## Coding of industries in the GSS

	Sector	GSS 1972 – 1988 1970 Census codes	GSS 1989 – 2006 1980 Census codes
1	Agriculture, forestry, fishery	17-28	10-31
2	Mining	47-57	40-50
3	Construction	67-77	60
4	Lumber, wood, furniture	107-118	230-242
5	Stone, clay, glass	119-138	250-262
6	Metal	139-169	270-301
7	Machinery, exc. electrical	177-198, 258	310-332
8	Electrical machinery	199-209	340-350
9	Transportation equipment	219-238	351-370
10	Professional equipment	239-259	371-382
11	Food and tobacco	268-299	100-130
12	Textile, apparel, leather	307-327, 388-397	132-152, 220-222
13	Paper	328-337	160-162
14	Printing	338-339	171-172
15	Chemicals	347-369	180-192
16	Petroleum and rubber	377-387	200-212
17	Other manufacturing	259, 398	390-392
18	Transportation	407-429	400-432
19	Communication	447-449	440-442
20	Utilities	467-479	460-472
21	Wholesale trade	507-588	500-571
22	Retail trade	607-698	580-691
23	Finance, insurance, real estate	707-718	700-712
24	Business services	727-748	721-742
25	Repair services	749-759	750-760
26	Personal services	769-798	761-791
27	Recreation services	807-809	800-802
28	Health	828-848	812-840
29	Legal services	849	841
30	Education	857-868	842-860
31	Religious and welfare services	877-879	861-871, 880
32	Other services	869, 887-897	872, 881-892
33	Public administration	907-937	907-937

## Coding of occupations in the GSS

	Occupation	GSS 1972 – 1988 1970 Census codes	GSS 1989 – 2006 1980 Census codes
1	Administrative and managerial	1, 56, 201-246	3-37
2	Engineers	2, 6-26	43-63
3	Math and computer scientists	2-5, 34-36, 55	64-68
4	Natural scientists	42-54	69-83
5	Health professionals	61-73	84-89
6	Health treatment occupations	74-76	95-106
7	Post-secondary teachers	102-140	113-154
8	Teachers, exc. post-secondary	141-145	155-159
9	Counsellors, librarians, archivists	32-33, 174	163-165
10	Social scientists, urban planners	91-96	166-173
11	Social and religious workers	86-90, 100, 101	174-177
12	Lawyers and judges	30-31	178-179
13	Writers, artists, athletes	175-194	183-199
14	Technicians and support occupations	80-85, 150-173	203-235
15	Sales occupations	260-296	243-285
16	Clerical and admin. support occupations	301-396	303-389
17	Private household workers	980-986	403-407
18	Protective services workers	960-976	413-427
19	Service workers, exc. 17 and 18	901-954	433-469
20	Farming occupations	801-846	473-499
21	Crafts and repair workers	401-586	503-699
22	Operators and laborers	601-796	703-889

## Coding of industries in the NHIS

Sector	NHIS 1974 - 1994		NHIS 1995-2003	NHIS 2004-2009
	1970 Census codes	1980 Census codes		
1 Agriculture, forestry, fishery	17-28	10-31	1, 2	1-5
2 Mining	47-57	40-50	10	6-8
3 Construction	67-77	60	20	10
4 Lumber, wood, furniture, stone, clay, glass	107-138	230-262	40	17, 30
5 Metal	139-169	270-301	41	24, 25
6 Machinery, exc. electrical	177-198, 258	310-339	43, 42	26
7 Electrical machinery	199-209	340-350	44	27, 28
8 Transportation equipment	219-238	351-370	45	29
9 Food and tobacco	268-299	100-130	30	11, 12
10 Textile, apparel, leather	307-327, 388-397	132-152,220-228	31	13-16
11 Printing and paper	328-339	160-175	32	18, 19, 50
12 Chemicals, petroleum, rubber	347-369, 377-387	180-219	33	20-22
13 Other manufacturing	239-259, 398	259,371-399	46, 34	31, 23
14 Transportation	407-429	400-439	50-52	47-49
15 Communication	447-449	440-449	53	52-53, 51
16 Utilities	467-479	450-499	54	9
17 Wholesale	507-588	500-579	60	32-34
18 Retail	607-698	580-699	61-65	35-46
19 FIRE	707-718	700-719	70-71	54-60
20 Business services	727-748	720-750	75	62
21 Repair services	749-759	751-760	76	74
22 Personal services	769-798	761-792	77-78	75
23 Recreation and entertainment	807-809	800-811	79	69-71
24 Health	828-848	812-840	80-81	65-68
25 Educational	857-868	842-861	82-83	64
26 Religious and welfare services	877-879	862-871,880	84	76
27 Other services, inc. legal	869, 887-897, 849	841,872-877,881-899	85	72, 73, 77, 61, 63
28 Public administration	907-937	900-990	90	78

## Coding of occupations in the NHIS

Occupations	NHIS 1974 - 1994		NHIS 1995-2003	NHIS 2004-2009
	1970 Census code	1980 Census code		
1 Administrative and managerial	1,200-249, 56	3-39	1-3	1-5
2 Engineers	2-27,34-55,57-58	42-83	4-6	7-10,12-13
3 Health professionals	60-73	84-89	7	29
4 Health treatment occs	74-79	90-106	8	32-34
5 Teachers	32-33,102-149,174	110-165	9	20-23
6 Other professional occs	30-31,86-101	166-179	11	14,16-19
7 Writers, artists, athletes	175-199	180-199	10	25-28
8 Technicians and support	80-85,150-173	200-239	12-13	11,15,30-31
9 Sales occupations	250-297	240-299	14-16	53-57
10 Clerical and admin support	301-399	300-399	17-21	58-64
11 Services: protective	950-989	413-432	23-24	35-38
12 Services: food	910-919	433-444	25	39-42
13 Services: cleaning, private hh	900-909,980-986	401-410,448-455	22,27	43-45
14 Services: personal	931-959	456-469	28	46-52
15 Services: health	921-930	445-447	26	32-34
16 Farming	801-846	470-499	29-31	65-68
17 Crafts and repair	400-599	500-699	32-34	74-77
18 Operators and laborers	600-798,848-899	703-899	35-41	78-93

**Table 1**  
**Regressions of Happiness on ln of Family Income for Men**  
**General Social Survey, 1972 – 2006**  
(Standard errors in parentheses)

Estimation method	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS	0.172 (0.015)	0.128 (0.015)	0.124 (0.016)	0.097 (0.015)	0.171 (0.015)	0.126 (0.015)	0.122 (0.016)	0.096 (0.015)
2SLS	0.266 (0.075)	0.187 (0.078)	0.293 (0.095)	0.303 (0.092)	0.265 (0.075)	0.182 (0.078)	0.295 (0.095)	0.305 (0.092)
IJIVE	0.276 (0.082)	0.192 (0.087)	0.321 (0.111)	0.335 (0.107)	0.275 (0.083)	0.187 (0.087)	0.323 (0.111)	0.338 (0.108)
First stage <i>F</i> -statistic	11.77	10.88	7.06	7.04	11.72	10.77	7.08	7.06
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
4 marital status dummies		✓	✓	✓		✓	✓	✓
21 occupation dummies			✓	✓			✓	✓
4 job satisfaction dummies				✓				✓
Mother's education				•	✓	✓	✓	✓

Weighted regressions using GSS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for black and other non-white race, eight education dummies, and 25 year dummies. Instruments are 32 industry dummies. Number of observations is 10,547. Heteroskedasticity robust standard errors in parentheses.

**Table 2**  
**Regressions of Happiness and Mother's Education on ln of Family Income for Men**  
**General Social Survey, 1972 – 2006**  
(Standard errors in parentheses)

Estimation method	Dependent Variable							
	Happiness				Mother's education			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OLS	0.172 (0.015)	0.128 (0.015)	0.124 (0.016)	0.097 (0.015)	0.166 (0.047)	0.220 (0.048)	0.173 (0.049)	0.165 (0.048)
2SLS	0.266 (0.075)	0.187 (0.078)	0.293 (0.095)	0.303 (0.092)	0.266 (0.244)	0.479 (0.257)	0.050 (0.306)	0.054 (0.307)
IJIVE	0.276 (0.082)	0.192 (0.087)	0.321 (0.111)	0.335 (0.107)	0.282 (0.268)	0.515 (0.286)	0.040 (0.355)	0.047 (0.356)
First stage <i>F</i> -statistic	11.77	10.88	7.06	7.04	11.77	10.88	7.06	7.04
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
4 marital status dummies		✓	✓	✓		✓	✓	✓
21 occupation dummies			✓	✓			✓	✓
4 job satisfaction dummies				✓				✓

Weighted regressions using GSS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for black and other non-white race, eight education dummies, and 25 year dummies. Instruments are 32 industry dummies. Number of observations is 10,547. Heteroskedasticity robust standard errors in parentheses.

**Table 3**  
**Regressions of Happiness on ln of Family Income for Married Men and Women**  
**General Social Survey, 1972 – 2006**  
(Standard errors in parentheses)

Estimation method	Dependent Variable									
	Happiness					Mother's education				
	Sample					Sample				
	Husbands	Wives	Wives, not working	Wives, working		Husbands	Wives	Wives, not working	Wives, working	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
OLS	0.189 (0.023)	0.105 (0.019)	0.114 (0.027)	0.102 (0.026)	0.103 (0.027)	0.387 (0.072)	0.314 (0.060)	0.391 (0.085)	0.245 (0.088)	0.217 (0.091)
2SLS	0.180 (0.109)	0.042 (0.080)	0.127 (0.103)	-0.010 (0.107)	0.010 (0.122)	0.654 (0.358)	0.777 (0.258)	0.564 (0.327)	0.537 (0.352)	0.431 (0.401)
IJIVE	0.179 (0.125)	0.036 (0.087)	0.126 (0.123)	-0.024 (0.124)	-0.003 (0.146)	0.688 (0.407)	0.824 (0.280)	0.605 (0.391)	0.587 (0.404)	0.482 (0.478)
First stage <i>F</i> -statistic	8.85	11.75	5.78	7.54	6.03	8.85	11.75	5.78	7.54	6.03
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
32 industry dummies (wives)					✓					✓
Number of observations	6,672	7,540	3,062	4,478	4,478	6,672	7,540	3,062	4,478	4,478

Weighted regressions using GSS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for black and other non-white race, eight education dummies, and 25 year dummies. Instruments are 32 industry dummies for husband's industry affiliation. Heteroskedasticity robust standard errors in parentheses.

**Table 4**  
**Comparison with Luttmer (2005)**  
**Men, General Social Survey, 1972 – 2006**  
(Standard errors in parentheses)

Estimation method	Dependent Variable					
	Happiness			Mother's education		
	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.172 (0.015)	0.172 (0.015)	0.172 (0.015)	0.166 (0.047)	0.166 (0.047)	0.166 (0.047)
2SLS	0.266 (0.075)	0.328 (0.072)	0.283 (0.048)	0.266 (0.244)	1.238 (0.239)	0.273 (0.143)
IJIVE	0.276 (0.082)	0.344 (0.077)	0.339 (0.071)	0.282 (0.268)	1.326 (0.256)	0.337 (0.213)
First stage <i>F</i> -statistic	11.77	20.64	3.19	11.77	20.64	3.19
Instruments	Industry	Occupation	Ind*Occ	Industry	Occupation	Ind*Occ

Weighted regressions of happiness on ln(family income) using GSS sampling weight. The coefficient on ln(family income) is displayed. All regressions include controls for age, age squared, dummies for black and other race, eight education dummies, and 25 year dummies. Instruments are 32 industry, 21 occupation dummies, or their interactions. Number of observations is 10,547. Heteroskedasticity robust standard errors in parentheses.

**Table 5**  
**Alternative Instruments Using Employer Differentials**  
**Men, General Social Survey, 1972 – 2006**  
(Standard errors in parentheses)

Estimation method	Dependent variable							
	Happiness				Mother's education			
	Instruments				Instruments			
	Union status	Firm size	Union and firm size	Union and industry	Union status	Firm size	Union and firm size	Union and industry
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
OLS	0.175 (0.018)	0.173 (0.022)	0.161 (0.026)	0.175 (0.018)	0.116 (0.056)	0.052 (0.073)	0.067 (0.091)	0.116 (0.056)
2SLS	0.242 (0.184)	0.208 (0.160)	0.321 (0.169)	0.274 (0.078)	-0.785 (0.603)	-0.435 (0.491)	-0.656 (0.553)	0.169 (0.251)
IJIVE	0.243 (0.187)	0.215 (0.175)	0.342 (0.190)	0.284 (0.086)	-0.798 (0.611)	-0.485 (0.538)	-0.749 (0.616)	0.174 (0.277)
First stage <i>F</i> -statistic	66.89	11.32	9.60	11.8	66.89	11.32	9.60	11.80
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Number of observations	7,365	4,444	3,082	7,365	7,365	4,444	3,082	7,365

Weighted regressions of happiness on ln(family income) using GSS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for black and other non-white race, eight education dummies, and 25 year dummies. Instruments are a dummy for union status, six dummies for firm size categories, and/or 32 industry dummies. Heteroskedasticity robust standard errors in parentheses.

**Table 6**  
**Regressions of Health and Height on ln of Family Income for Men**  
**NHIS, 1974-2009**  
 (standard errors in parentheses)

Estimation method	Dependent variable					
	Health			Height		
	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.135 (0.002)	0.130 (0.002)	0.124 (0.002)	0.770 (0.018)	0.781 (0.018)	0.731 (0.019)
2SLS	0.071 (0.010)	0.060 (0.010)	0.097 (0.012)	1.017 (0.088)	0.991 (0.091)	1.241 (0.114)
IJIVE	0.071 (0.010)	0.060 (0.010)	0.097 (0.013)	1.018 (0.088)	0.992 (0.091)	1.242 (0.115)
First stage F-statistic	493.3	478.0	333.7	493.3	478.0	333.7
Baseline controls	✓	✓	✓	✓	✓	✓
4 marital status dummies		✓	✓		✓	✓
17 occupation dummies			✓			✓

Weighted regressions using NHIS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for non-white, six education dummies, three region dummies, and 25 year dummies. Instruments are 27 industry dummies. Number of observations is 458,601. Heteroskedasticity robust standard errors in parentheses.

**Table 7**  
**Regressions of Health and Height on ln of Family Income for Men Aged 20-29**  
**NHIS, 1974-2009**  
 (standard errors in parentheses)

Estimation method	Dependent variable					
	Health			Height		
	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.095 (0.003)	0.094 (0.003)	0.093 (0.003)	0.606 (0.031)	0.607 (0.031)	0.572 (0.031)
2SLS	0.061 (0.016)	0.048 (0.016)	0.076 (0.020)	0.867 (0.155)	0.874 (0.156)	0.805 (0.197)
IJIVE	0.061 (0.016)	0.047 (0.016)	0.076 (0.020)	0.869 (0.156)	0.876 (0.157)	0.808 (0.199)
First stage F-statistic	114.2	113.9	67.98	114.2	113.9	67.98
Baseline controls	✓	✓	✓	✓	✓	✓
4 marital status dummies		✓	✓		✓	✓
17 occupation dummies			✓			✓

Weighted regressions using NHIS sampling weight. The coefficient on ln(family income) is displayed. Baseline controls are age, age squared, dummies for non-white, six education dummies, three region dummies, and 25 year dummies. Instruments are 27 industry dummies. Number of observations is 121,344. Heteroskedasticity robust standard errors in parentheses.

**CENTRE FOR ECONOMIC PERFORMANCE**  
**Recent Discussion Papers**

1162	Cletus C. Coughlin Dennis Novy	Is the International Border Effect Larger than the Domestic Border Effect? Evidence from U.S. Trade
1161	Gianluca Benigno Luca Fornaro	Reserve Accumulation, Growth and Financial Crises
1160	Gianluca Benigno Huigang Chen Christopher Otrok Alessandro Rebucci Eric R. Young	Capital Controls or Exchange Rate Policy? A Pecuniary Externality Perspective
1159	Paul Dolan Georgios Kavetsos	Happy Talk: Mode of Administration Effects on Subjective Well-Being
1158	Alan Manning	Steady-State Equilibrium in a Model of Short-Term Wage-Posting
1157	Joan Costa-Font Mireia Jofre-Bonet Steven T. Yen	Not all Incentives Wash out the Warm Glow: The Case of Blood Donation Revisited
1156	Christian Siegel	Female Employment and Fertility - The Effects of Rising Female Wages
1155	Albrecht Ritschl	The German Transfer Problem, 1920-1933: A Sovereign Debt Perspective
1154	Gabriel M. Ahlfeldt Stephen J. Redding Daniel M. Sturm Nikolaus Wolf	The Economics of Density: Evidence from the Berlin Wall
1153	Nattavudh Powdthavee Yohanes E. Riyanto	Why Do People Pay for Useless Advice?
1152	Thomas Sampson	Selection into Trade and Wage Inequality
1151	Tim Barmby Alex Bryson Barbara Eberth	Human Capital, Matching and Job Satisfaction
1150	Ralf Martin Mirabelle Muûls Laure de Preux Ulrich J. Wagner	Industry Compensation Under Relocation Risk: A Firm-Level Analysis of the EU Emissions Trading Scheme
1149	Albrecht Ritschl	Reparations, Deficits, and Debt Default: the Great Depression in Germany

1148	Alex Bryson John Forth Minghai Zhou	The CEO Labour Market in China's Public Listed Companies
1147	Gianmarco I. P. Ottaviano Giovanni Peri Greg C. Wright	Immigration, Offshoring and American Jobs
1146	Thierry Mayer Marc J. Melitz Gianmarco I. P. Ottaviano	Market Size, Competition, and the Product Mix of Exporters
1145	Oriana Bandiera Luigi Guiso Andrea Prat Raffaella Sadun	What do CEOs Do?
1144	Oriana Bandiera Luigi Guiso Andrea Prat Raffaella Sadun	Matching Firms, Managers, and Incentives
1143	Michael Boehm Martin Watzinger	The Allocation of Talent over the Business Cycle and its Effect on Sectoral Productivity
1142	Johannes Spinnewijn	Heterogeneity, Demand for Insurance and Adverse Selection
1141	Raphael Calel Antoine Dechezleprêtre	Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market
1140	Stephen J. Redding	Goods Trade, Factor Mobility and Welfare
1139	Oriana Bandiera Andrea Prat Raffaella Sadun Julie Wulf	Span of Control and Span of Activity
1138	Elhanan Helpman Oleg Itskhoki Marc-Andreas Muendler Stephen Redding	Trade and Inequality: from Theory to Estimation
1137	Andrew B. Bernard Marco Grazzi Chiara Tomasi	Intermediaries in International Trade: Direct versus Indirect Modes of Export
1136	Ghazala Azmat Rosa Ferrer	Gender Gaps in Performance: Evidence from Young Lawyers

**The Centre for Economic Performance Publications Unit**  
**Tel 020 7955 7673 Fax 020 7955 7595**  
**Email [info@cep.lse.ac.uk](mailto:info@cep.lse.ac.uk) Web site <http://cep.lse.ac.uk>**