THE IMPACT OF MINIMUM WAGES ON JOB TRAINING: AN EMPIRICAL EXPLORATION WITH ESTABLISHMENT DATA

by

David Fairris*
University of California at Riverside

and

Roberto Pedace*
University of Redlands

CES 03-04 February, 2003

Abstract

Human capital theory suggests that workers may finance on-the-job training by accepting lower wages during the training period. Minimum wage laws could reduce job training, then, to the extent they prevent low-wage workers from offering sufficient wage cuts to finance training. Empirical findings on the relationship between minimum wages and job training have failed to reach a consensus. Previous research has relied primarily on survey data from individual workers, which typically lack both detailed measures of job training and important information about the characteristics of firms. This study addresses the issue of minimum wages and on-the-job training with a unique employer survey. We find no evidence indicating that minimum wages reduce the average hours of training of trained employees, and little to suggest that minimum wages reduce the percentage of workers receiving training.

* The authors thank Bill Carter, David Merrell, Mark Mildorf, Arnie Reznek, and Mary Streitwieser for their help in acquiring and creating the data. Robert Breunig, Craig Gundersen, David Neumark, Paul Sicilian, Jeffrey Wooldridge, and participants of the Claremont McKenna College and UC-Riverside seminar series provided valuable comments and suggestions on previous drafts of this paper. Financial support was provided by the UC Institute for Labor and Employment. The data used are confidential under Title 13 and 26, United States Code. Access was obtained through the Center for Economic Studies (CES) at the U.S. Census Bureau. Researchers can access this version of the National Employer Survey with a CES-approved proposal (see http://www.ces.census.gov/ces.php/home). A public-use version of the data is available (see http://www.irhe.upenn.edu/research/research-main.html). The findings and opinions expressed do not reflect the position of the institutions represented by the authors, the National Center for Postsecondary Improvement, the Consortium for Policy Research in Education, the National School-to-Work Office, or the U.S. Census Bureau.

1. Introduction

Human capital theory suggests that workers must contribute towards investments in job training, and that one way in which they might do so is through reduced wages (Becker 1964). Minimum wage laws might be expected to reduce on-the-job training, then, to the extent they prevent workers from accepting lower wages (Rosen 1972).[1] Existing empirical studies of the relationship between minimum wages and job training yield divergent results. However, most of these studies utilize worker survey data that lack detailed measures of job training and establishment-level variables that are important determinants of training. In this paper, we overcome these problems by using an establishment data set that possesses both good measures of job training and good establishment-level control variables.

The decision to offer training is ultimately made by the firm. Even if workers pay for some or all of their training through the acceptance of lower wages, their decision to undertake training is made largely by the choice of which firm to join. Thus, we believe the firm is the logical unit of analysis for exploring the issue of job training and minimum wages.

In the first section of the paper, we review the empirical literature on the impact of minimum wages on job training. The second and third sections discuss the empirical specification and data to be used in the analysis. The fourth section discusses the empirical results. We find little evidence linking minimum wages to reductions in the percentage of the establishment workforce receiving training, and absolutely no evidence linking them to reduced hours of training per trained worker.

---

[1] Workers and employers are likely to share in the costs of training, but the relative contributions depend on the type of training acquired. Typically, workers' relative contributions will be greater with general training because the rewards to these skills can be reaped with numerous employers. Firm-specific training, on the other hand,

2. Review of the Literature

The empirical literature on the impact of minimum wages on job training is not voluminous. The earliest efforts focused primarily on wage growth as a proxy for training, producing mixed results. Two studies found age-earnings profiles to be significantly flatter for workers whose wages were bound to the minimum (Leighton and Mincer 1981; Hashimoto 1982), while a third study (Lazear and Miller 1981) found no statistically significant relationship between minimum wages and the slope of age-earnings profiles. Recent evidence has cast serious doubt on the validity of this entire approach.

Grossberg and Sicilian (1999) find that while minimum wages are indeed associated with reduced wage growth, they appear to have no significant impact on job training. Acemoglu and Pischke (1999) offer an insightful interpretation of these results. They claim that minimum wages eliminate part of the lower tail of the wage distribution, bunching workers around the wage minimum and thereby lowering the age-earnings profile quite independent of their impact on training. Thus, it seems clear that valid tests of the relationship between minimum wages and job training must be conducted with information on worker training and not simply wage growth.

There are only five empirical studies offering evidence on the impact of minimum wages directly on job training. The basic approach is to regress a measure of job training on a set of explanatory variables and a variable capturing the degree to which minimum wages act as a constraint on wage reductions. The hypothesis is that the more binding the minimum wage constraint, the less job training the worker and firm will undertake. There exist two levels of analysis in the literature, one operating at the state or regional level and the other operating at the level of the individual worker. Both have flaws.

---

usually requires a smaller relative investment from workers. Minimum wages should therefore have a larger effect

Leighton and Mincer (1981) and Neumark and Wascher (2001) exploit variation in state wage minimums to explore the relationship between minimum wages and training. Both use data on individual workers, but their measures of the minimum wage exist at the state level. For example, Neumark and Wascher use the extent to which the state minimum wage exceeded the federal minimum over the previous three years. The results of both studies suggest that the higher the state minimum wage, the less likely it is that workers will receive on-the-job training.

However, there are several econometric problems plaguing this approach. First, these studies use state-level measures of minimum wages with individual-level data. Because the minimum wage variable exists at a higher level of aggregation than the unit of observation, the estimated standard error may understate the inaccuracy of the estimated coefficient (Moulton 1986), leading the researcher to perhaps mistakenly conclude that minimum wages reduce training when in fact they do not. A second concern is that the minimum wage variable may capture unobserved state effects on training that are correlated with minimum wages.[2]

Another approach to analyzing the impact of minimum wages on job training utilizes individual level data only. Schiller (1994) and Grossberg and Sicilian (1999) adopt measures of the degree to which wages are bound by the minimum wage that vary at the level of the individual worker. Grossberg and Sicilian, for example, compare the impact on training of workers who are paid the minimum wage with those who earn both below the minimum and slightly more than the minimum. Schiller finds evidence that minimum wages reduce training, whereas Grossberg and Sicilian do not.

---

on general training, where the cost/wage contributions by workers are the greatest.

[2] Neumark and Wascher use a difference-in-difference approach that allows them to add state controls. We employ this technique in some of our empirical results below, and discuss more fully at that time our concerns with this specification of the training equation.

The problem with using minimum wage measures that vary at the level of the individual worker is that omitted determinants of training are likely to be correlated with the wage, which itself is used to assess the degree to which the minimum wage is binding. The estimated impact of minimum wages on training may well be biased as a result, the nature of the bias depending on the exact specification employed. For example, while it is possible that binding minimum wages reduce training, it is most probable that job training raises wages and thereby makes workers' wages less bound by the minimum wage. The wage component of the minimum wage measure is, therefore, likely to be correlated with left-out determinants of training, biasing the estimated impact of minimum wages on training. And, here, the bias is likely to be upward.[3]

Acemoglu and Pischke (1999) conduct a first-difference analysis of the individual worker training equation using panel data. Fixed components of the error term will be eliminated in this approach, thereby reducing the possible bias found in cross-sectional levels regressions. Acemoglu and Pischke find no evidence of a training effect of minimum wages in their results. However, their measure of on-the-job training is also a particularly blunt one – namely, the change in whether or not the worker received job training at the current firm.

Indeed, poor measures of job training plague this literature more generally. Probably the most common measure of training is a dichotomous variable indicating its existence or lack thereof. An important exception is the Grossberg and Sicilian (1999) study, which utilizes data from establishments. The job training information they use refers to the amount of job training given to the last-hired worker. Specifically, their training measure is the number of hours devoted to training over the first three months of tenure of the most recently hired worker.

[3] The Grossberg and Sicilian results are not subject to this type of bias because they use the starting wage of the worker.

However, Grossberg and Sicilian are unable to account for many important establishment-level determinants of training.

In this paper, we utilize a unique data set on establishments that offers an interesting alternative to the data used in most of the existing literature. First, we have good measures of job training – the percentage of the work force receiving training and the average hours of training conditional on receiving training. Second, we possess good measures of a number of establishment-level control variables, including labor turnover and employee fringe benefits levels, that are absent from most existing studies.

Efficiency wage theory suggests that firms may reduce costly turnover by paying higher wages (Akerlof and Yellen 1986). Thus, wages (and therefore the extent to which wages are bound by the minimum wage) may be negatively correlated with turnover. But, turnover reduction may also be a prerequisite for on-the-job training (Prendergast 1993), and so an important determinant in the training equation. If turnover is related to both the measure of the minimum wage and to job training in the way we have claimed, the failure to control for turnover may bias upward the estimated impact of minimum wages on training. It is important to control for fringe benefits in an analysis of the minimum wage impact on training because training could be financed by accepting lower benefits levels rather than by accepting lower wages.

Economies of scale in training and a host of other considerations suggest to us that job training is likely to exist as a matter of policy at the establishment or firm level, thereby making the establishment the appropriate unit of analysis for any investigation of job training. Workers receive training by virtue of the firm to which they attach themselves. Focusing on the determinants of training solely from the worker's point of view might make sense in a world of costless mobility, where the public-good nature of training poses no real problem for individual choice (Tiebout 1956). But, the very mention of job training typically suggests a context in which there is greater attachment between worker and firm than ideal microeconomics models posit, and therefore in which firm policy and firm-level variables matter.

3. Econometric Specification

The empirical approach we take resembles that of the existing literature, but we use two different measures of job training and incorporate a wide range of establishment-level control variables into the analysis. We begin with a simple training equation of the following form:

$$t_{js} = \alpha + \mathbf{x}'_{js}\boldsymbol{\beta} + m_s\psi + \varepsilon_{js} \qquad (1)$$

where t_{js} is a measure of the job training provided by establishment j in state s, $\mathbf{x}_{js}$ is a vector of establishment characteristics (e.g., industry, workforce size, percent of female workers, percent of workers with a high school diploma, turnover, fringe benefits, etc.), and m_s is the difference between the state minimum wage and the federal minimum wage.[4]

In order to employ this measure of the minimum wage, we identify states with minimum wages above the federal minimum and assign to establishments in those states the value of the difference between the state and federal minimums; all remaining establishments receive a zero for this variable. In this specification, the minimum wage variable is measured at a higher level of aggregation (the state level) than is the unit of observation (the establishment level). Under

[4] Aside from the minimum wage measure, the specification of the training equation closely resembles that of Lynch and Black (1998) who utilize an earlier version of the NES data.

such circumstances, the standard assumption of uncorrelated errors across the observations is violated, and the error structure will have the following form:

$$\varepsilon_{js} = \lambda_s + \varphi_{js} \tag{2}$$

This may lead to possible downward bias in the standard errors of the estimated minimum wage effect, thereby allowing one to mistakenly find in favor of a statistically significant effect on training when no such effect exists. We therefore correct, in all of our results below, the standard errors for this "clustering" of observations at the state level using the technique recommended by Moulton (1986).

Another concern with this approach is that the minimum wage measure may capture state effects on training that are correlated with minimum wages. Suppose, for example, that states with higher minimum wages also possess policies – such as training subsidies or employment programs that yield better job matches – that lead to greater incentives for training by firms. In this case, the absence of state controls will tend to result in an underestimation of the negative effect of minimum wages on training.

To address this concern, we estimate the training equation utilizing a difference-in-difference estimation technique, similar to that of Neumark and Wascher (2001), which allows for the inclusion of state controls. Thus, the training equation becomes:

$$t_{ijs} = \alpha + \mathbf{x}'_{js}\boldsymbol{\beta} + \mathbf{s}'_{s}\boldsymbol{\gamma} + \mathbf{d}'_{ijs}\boldsymbol{\delta} + \mathbf{i}'_{ijs}\boldsymbol{\psi} + \varepsilon_{ijs} \tag{3}$$

where t_{ijs} is a measure of training for occupation group *i* at establishment *j* in state *s*, $\mathbf{x}_{js}$ is a vector of establishment characteristics as in equation (1), $\mathbf{s}_s$ is a vector of state dummy variables, $\mathbf{d}_{ijs}$ is a vector of dummy variables representing the occupation from which the observation was drawn, and $\mathbf{i}_{ijs}$ is a vector of interactions between the occupation dummies and the minimum wage measure used in equation (1). Assuming the training of managerial workers is unlikely to be affected by the minimum wage, they can be used as the base category in the vector of interactions. Controlling for state fixed effects, the causal effect of the minimum wage is captured by $\boldsymbol{\psi}$, which reports the differential impact of the minimum wage on occupational categories which are more likely to be affected relative to an occupational category – namely, managerial workers – that is unlikely to be affected.

One drawback to this approach is that it assumes the unobservables – state policy, for example – that are correlated with both the minimum wage and training have the same effect on all the occupational estimates of the minimum wage impact on training. This might be a quite restrictive assumption given that states with high minimum wages are also arguably more likely to possess active labor market policies that disproportionately affect the training needs of low skill workers. In addition, we must also restrict all of the establishment characteristics to have the same effect on training for all occupational groups.

Another drawback, one which the difference-in-difference approach shares with the specification in equation (1), is that the minimum wage variable is a rather blunt measure of the extent to which minimum wages are binding on establishments. This measure varies only at the state level, and indeed only among those states with minimum wages greater than the federal minimum.

Thus, in a final specification of the training equation, we utilize a measure of minimum wages that operates at the establishment and occupation level rather than state level. This training equation is as follows:

$$t_{ijs} = \alpha_i + \mathbf{x}'_{js}\boldsymbol{\beta}_i + \mathbf{s}'_s\boldsymbol{\gamma}_i + \frac{m_s}{w_{ijs}}\psi_i + \varepsilon_{ijs} \tag{4}$$

where t_{ijs} is a measure of training for occupation group *i* at establishment *j* in state *s*, $\mathbf{x}_{js}$ is a vector of establishment characteristics as in equations (1) and (3), $\mathbf{s}_s$ is a vector of state dummies as in equation (3), m_s is the applicable state minimum wage, and w_{ijs} is the average wage for the occupation in each establishment.[5] The *i* subscripts on the parameters indicates that the training equation is estimated individually for each occupational category.

This approach identifies the minimum wage impact on training by exploring whether establishments whose average establishment or occupation wage is closer to the state minimum wage offer less training. Unfortunately, this approach raises a number of challenging specification issues. Most importantly, it is plagued by the presence of the establishment wage on the right-hand-side of the training equation. While the extent of job training may be related to how bound wages are to the minimum wage, it is also true that training affects wages. Thus, left out determinants of training may be correlated with the establishment average wage. Where

[5] Acemoglu and Pischke (1999) construct a similar variable that measures the ratio of the minimum wage to the average wage in the MSA (Metropolitan Statistical Area). However, since wages can vary considerably within MSAs, even less aggregation may be appropriate. We construct a minimum wage measure that captures the extent to which workers in given occupational groups are, on average, bound by the minimum wage at their place of employment.

necessary, then, we must correct for endogeneity bias by instrumenting the average wage variable, raising all of the attendant problems and pitfalls such a correction entails.

A final concern we have with all the estimated training equations stems from the high incidence of censoring among the establishment responses to the survey questions on training. Roughly 17 percent of the establishments in our sample report that they offer no training at all to their workers and approximately 16 percent report that they train all of their workers. This clustering of values for the dependent variable raises the possibility of censored regression bias in our results. To correct for this, we estimate both training equations with a Tobit maximum likelihood estimation technique, and report these results as well.[6] The "hours of training" regressions are estimated with lower limit censoring and the "percent trained" regressions are estimated with both lower and upper limit censoring.

4. Data

This study utilizes the 1997 National Employer Survey (NES), supplemented with Standard Statistical Establishment List (SSEL) data. The SSEL is the Census Bureau's master list of all establishments and enterprises in the United States. It provides the sampling frame for the Census Bureau's economic censuses and surveys, including the NES. We use the SSEL to establish the geographical location of firms in our survey, without which we would be unable to

[6] Papke and Wooldridge (1996) suggest the use of a quasi-maximum likelihood logit estimator (QMLE) for fractional response dependent variables. In the case of our "percent trained" variable, the Tobit and QMLE both provide different, but reasonable functional forms for the conditional mean. The advantage of the QMLE is that it only requires specification of the conditional mean, while the Tobit requires the specification of the entire distribution and, therefore, relies heavily on the normality (and joint normality) assumptions. The Tobit estimates can be sensitive to specification, but the QMLE provides consistent estimates even in the presence of functional form misspecification (Johnston and DiNardo 1997; Papke and Wooldridge 1996). We check the robustness of our Tobit estimates by also estimating equation (3) and equation (4) with a QMLE.

assign the relevant minimum wage level to each surveyed firm. The 1995 SSEL serves as the sampling frame for the 1997 NES.

Survey data were collected with a computer-assisted telephone interview (CATI). The sample was evenly divided between manufacturers and non-manufacturers, with explicit over-sampling of establishments that have 100 or more employees and implicit over-sampling of manufacturers because they are greatly outnumbered by non-manufacturers in the SSEL universe. Establishments in California, Kentucky, Maryland, Michigan, and Pennsylvania were also over-sampled in order to support in depth analysis of school reforms of interest to the survey sponsors (the National Center for Postsecondary Improvement, the Consortium for Policy Research in Education, and the National School-to-Work Office).

The survey was administered by the U.S. Census Bureau in the summer of 1997, and asked establishments about conditions in 1996.[7] It represents the responses of approximately 5,400 establishments for a 78 percent overall response rate. This is higher than the response rate for other establishment surveys, but is similar to that of the 1994 NES (Lynch and Black 1998). After deleting observations with missing values on the variables of interest, we were left with 1,098 valid observations. All of our descriptive statistics and regression results are calculated from this sample of firms. The presence of over-sampled establishments requires the use of the provided weights in order to produce representative statistics and parameter estimates. Table 1 displays the minimum wage in cases where the state minimum exceeded the federal minimum. Table 2A provides descriptive statistics for the variables used in the analysis.

[Insert Table 1 and Table 2A]

[7] In October 1996 the federal minimum wage increased from $4.25 to $4.75, so we assign a weighted average to represent the minimum wage for that year.

While previous studies often rely on dichotomous measures of training (e.g., whether or not the individual received training), the NES offers two detailed measures of job training: the "percent of workers trained" and the "average number of hours devoted to training" in the establishment. The survey questions regarding job training begin with the following statement:

> I am now going to ask you some questions about structured or formal training that your employees experience. This training may be offered at your establishment or at another location, and may occur during working hours or at other times. Structured training includes all types of training activities that have a pre-defined objective. Examples of structured or formal training include seminars, lectures, workshops, audio-visual presentations, apprenticeships, and structured on-the-job training.

This is followed by specific questions regarding training:

> In the past year, how many workers received formal instruction, and what was the approximate average number of hours of training per employee?

The responses to this question are used to construct our dependent training measures.

Tables 2B and 2C provide descriptive measures of training by occupation and firm size, respectively.[8] While the support staff in the average establishment receives markedly less training than do supervisors, in general there is less variation across occupational categories in both the percent of workers trained and the average hours of training than was expected. Training investments vary by establishment size in the expected way – namely, there exists more training in larger establishments.

[Insert Table 2B and Table 2C]

The data set contains measures of labor turnover and a host of other variables that affect the firm's decision to offer training. Some, such as the gender and racial composition and average level of schooling of the workforce, mirror the kinds of variables one finds in estimated training regressions using worker-level survey data. Others, such as the quality of the local high school, are important worker-related determinants of job training that are rarely found in individual survey data.[9] And still others, such as whether the establishment has recently increased employment or is experimenting with new forms of workplace organization (e.g., self-managed teams or job rotation), are establishment-level variables that clearly impact training, but are virtually impossible to obtain from worker survey data.

5. Results

In Table 3, we present the results of OLS training regressions using the specification in equation (1).[10] In Table 4, the results from the difference-in-difference specification in equation (3) are presented, with managerial workers as the base occupation. The estimated coefficients for the various control variables are omitted in order to conserve space. (See Appendix A for estimated coefficients of the other explanatory variables from the column (1), Table 4 results).

The results in the first row of column (1), Table 3, suggest that establishments in states with minimum wages that exceed the federal minimum train a smaller percentage of their workforce. The estimated effect is not only statistically significant, but quantitatively significant as well. A fifty-cent increase in the state minimum wage, holding the federal minimum wage constant, reduces the fraction of workers receiving training by over 15 percentage points. Evaluated at the mean, this translates into roughly a 25 percent reduction in the fraction of workers receiving training.

---

[8] Note, however, that we do not have the ability to distinguish general training from firm-specific training.

[9] The quality of the local high school may affect how much firms rely on in-house training programs for the transmission of basic skills. This effect will be less significant to the degree that workers migrate across district boundaries.

[10] Given Royalty's (1996) and Grossberg's (2000) results, we were concerned about possible endogeneity bias in the estimated coefficient on labor turnover. However, Hausman-Wu tests (Greene 2000) failed to reject the null hypothesis of exogeneity in any of the results we present below. Turnover was instrumented with the "percent of workers unionized" as the identifying variable.

[Insert Table 3]

In the first row of column (2) we present the results for the "average hours of training" regression. In this regression, the estimated coefficient on the minimum wage variable is not statistically significantly different from zero. Thus, while minimum wages reduce the percentage of the workforce receiving training in this specification, they appear to have no impact on the average hours of training among trained employees.

Greater insight into these results may be achieved through an analysis of the job training impact of minimum wages on specific occupational groups. In the column (2) results, although average hours of training for the trained workforce as a whole do not appear to change in response to the minimum wage, it is possible that some occupational groups receive fewer hours of training while other occupational groups receive more hours of training as the minimum wage becomes more binding in a plant. This is entirely consistent with theory, which predicts that, in response to a minimum wage, employers may upgrade their technology of production and invest greater amounts of job training in fewer, more highly skilled workers. The lost training for those low-skilled workers who are finance constrained by the existence of minimum wages are merely transferred to more highly-skilled, less finance-constrained workers. While our occupational categories are rather broad, and so may disguise training substitution effects of this sort within occupations, we find no evidence in the occupation-specific results of column (2) to suggest that some workers receive greater training as the result of more binding minimum wages.

Turning to the column (1) results, we see that the reduction in the percentage of workers trained as a result of greater minimum wages takes place across the occupational distribution: among front line workers and technical workers, but also among management, the highest-paid of the occupational categories. Because we expect that minimum wages are unlikely to affect the training of managerial workers, this finding seems to us an indication that the results of this specification are tainted by omitted-variable bias.

[Insert Table 4]

In Table 4 we present the results of the difference-in-difference approach, which, because it focuses on relative training effects, allows us to net out the effect of unobservables that may be producing bias in the results of Table 3 by adding state effects. The results from column (1) of Table 4 suggest that the relative percent of workers trained is not affected for any of the included occupational groups by a difference between the state and the federal minimum wage. In column (2), the results are presented for the "average hours of training" regression. In this regression, the estimated relative minimum wage effects are also insignificantly different from zero, and the quantitative impacts on training are extremely small. Possessing a state minimum wage that is higher than the federal minimum by fifty cents decreases the training of front line workers relative to managers by roughly one percentage point.

While none of the estimated coefficients in Table 4 is statistically significant, the alternating negative/positive pattern is interesting and perhaps suggestive of substitution effects of the minimum wage on training. Interestingly, the alternating positive/negative pattern is exactly the opposite in the percent trained and average hours trained regressions, which suggests that when the minimum wage causes firms to train fewer workers, firms increase the average hours of training of those workers who continue to receive training.

Ultimately, though, these results suggest that minimum wages have absolutely no effect on either the extensive (percent of workers trained) or intensive (hours of training per trained employee) margins. Thus, the difference-in-difference results offer considerable evidence to suggest that the Table 3 results are biased.

The integrity of the difference-in-difference results rests on the assumption that unobservables such as state policy affect the impact of minimum wages on training similarly for every occupational group. However, there are reasons to believe this assumption may be in error, suggesting that we attempt to identify the minimum wage impact on training separately for each occupation. Moreover, both the difference-in-difference specification and the simple state-level specification of equation (1) utilize a minimum wage measure that is especially blunt in that it varies at the state level only, and indeed only for states that have enacted a minimum wage higher than the federal minimum.

The results reported in Table 5 utilize an alternative minimum wage variable, one that measures the extent to which state minimum wages are binding for workers in a given firm and occupation, and incorporates state fixed effects whose impacts vary across occupational categories. The challenge posed by estimating this specification of the training equation is that the average wage variable must be instrumented in order to avoid endogeneity bias. We have used the "percent of workers unionized" and the "natural log of total sales" in the establishment as identifying variables in this instrumental variables (IV) procedure. While unions affect wages, and thereby training levels indirectly, they seldom have direct effects on training through collective bargaining agreements. Higher sales may affect wages through rent-sharing, but should not affect training directly.

Results from Generalized Method of Moments specification tests suggest that these are indeed valid identifying variables in the overall system of structural equations (Hausman 1978; Newey 1985). They are statistically significant determinants of average wages across establishments, but have no independent effect on training other than through their impact on average wages. We have utilized the instrumental variables procedure only when a Hausman test revealed statistically significant evidence of endogeneity bias in the OLS regression results. [11]

The results in column (1) indicate that there are negative minimum wage effects on training for the workforce as a whole, and that these negative effects are restricted to two of the occupational groups. Specifically, support staff and supervisory workers appear to witness statistically significant reductions in the percent of workers trained as a result of higher minimum wages. A fifty-cent increase in the minimum wage, *ceteris paribus*, reduces the fraction of support staff and supervisory workers receiving training by roughly 8 and 3 percentage-points, respectively. Evaluated at the mean, this translates into a 15 percent reduction for support staff workers and a 5 percent reduction for supervisory workers. The results in column (2) lend support to earlier findings suggesting that minimum wages have no effect on the hours that workers are trained.

[Insert Table 5]

The largest of the estimated minimum wage effects on training is for support staff workers, which is consistent with their economic position in the firm. Of the five occupational categories that can be identified with our data, this occupation has the lowest average wage and therefore should be most bound by the minimum wage. However, the negative estimated effect for supervisory workers, although smaller, is not as easily explained. The average wage of supervisory workers is significantly larger than that of either support staff or front line workers.

While we believe this specification has several virtues that the other specifications lack, we are also less than fully satisfied with the IV procedures employed and with the robustness of our findings. The establishment unionization rate, for example, is an important determinant of

[11] We reject the null hypothesis of exogeneity in only 2 of the 10 regressions. In all but these two cases, then, we

front line or technical workers' pay, but less so of manager or supervisor pay, and yet the minimum wage bindingness variable exhibited no signs of endogeneity bias in either of the former two occupational training regressions, but did so in the supervisor training regression.

More importantly, the only two instances in which we find evidence of a negative training effect of minimum wages among the occupation regressions are the two cases in which Hausman tests revealed the need for an IV procedure. The OLS estimated coefficients on the bindingness variables in these two cases are far from statistically significant, and their magnitudes are smaller by ten-fold than the IV results. While we have followed strict statistical procedures in arriving at these estimates, the dramatic change in magnitudes when IVs are used, coupled with the fact that negative and statistically significant training effects are found only in those instances where instrumental variables are employed, leave us with some concern for the integrity of these results.

In Tables 6 and 7, we replicate the regressions of Tables 4 and 5, but correct for the censored nature of the dependent variable using a Tobit estimation procedure.[12] Qualitatively, the results are entirely consistent with the regressions that ignore the censored nature of the dependent variable. As in Table 4, the Table 6 results suggest that minimum wages do not alter the percentage of the establishment workforce receiving training or the hours of training per employee.[13]

[Insert Table 6]

---

are able to treat the average wage as exogenous.

[12] In order to compare the Tobit results to the uncensored estimates, they must be multiplied by an adjustment factor. The estimated effect is given by $\frac{\delta E[t \mid \bullet]}{\delta m} = \Phi\left(\frac{\hat{t}}{\sigma}\right)\psi$, where Φ is the standard normal cumulative distribution function and $\hat{t}$ is calculated using the mean values for the explanatory variables. For ease of interpretation, this adjustment factor is included in each of the relevant tables.

For the Table 7 regressions, in cases where the average wage must be instrumented, the nonlinear nature of the Tobit estimates requires that we give special attention to the standard errors. There are two instances where a two-stage estimation is required – the "percent trained" regressions for support staff and supervisory workers. Murphy and Topel (1985) define a covariance matrix for the nonlinear least squares estimator that accounts for the variability in the explanatory variable that is introduced through the two-step procedure.[14] However, our first stage regressions are used to obtain predicted values for the average establishment wage, which are then used to construct our establishment-level minimum wage measure. Consequently, the Murphy-Topel correction is not directly applicable in this case. In the two instances in which we utilize a two-stage Tobit estimation, we account for the variation in the first stage and correct the standard errors using a bootstrap procedure. This has been shown to produce reliable standard error estimates when these cannot be derived analytically (Johnston and DiNardo 1997).[15]

[Insert Table 7]

Nevertheless, we continue to find statistically significant negative minimum wage effects for support staff and supervisory workers. Moreover, quantitatively, the estimated impacts of minimum wages on training using the Tobit specification are larger. In the Table 5 results, for example, a fifty-cent difference between the state and federal minimum wages reduces the fraction of support staff workers receiving training by 8 percentage-points. This compares with

---

[13] Our QMLE results yield the same conclusions – there are no significant minimum wage effects on training.
[14] Generally, this adjustment leads to an increase in the computed standard errors.
[15] Jeong and Maddala (1993) have argued that most applications using standard errors for the purpose of hypothesis testing are useless due to unreliable distributional assumptions and should, therefore, use the bootstrap method directly.

a 17 percentage-point reduction in Table 7. Once again, there are no significant minimum wage effects on hours of training.[16]

6. Conclusions

This study utilizes establishment-level data to explore the impact of minimum wages on job training. The decision to offer training ultimately rests with firms, and so we believe the firm is the logical unit of analysis for exploring this issue. Using establishment data provides the opportunity to control for establishment-level variables, such as turnover and the provision of fringe benefits, which have been absent from previous analyses of training due to the reliance on individual worker data.

In our view, problematic specification issues plague all existing approaches to the estimation of the impact of minimum wages on job training, ours included. Nonetheless, one finding that is consistent across all specifications of the training equation is that minimum wage policies have no significant impact on the average hours of training for workers who receive training. The evidence on whether minimum wages reduce the percentage of the workforce receiving training is more mixed. Among occupations for which it is plausible to expect a negative minimum wage impact on training, only support staff workers exhibited such an effect, and only in one of the three specifications of the training equation we estimated. Therefore, we think the most prudent conclusion to draw from this set of findings is that there is little evidence to suggest that minimum wages affect the percentage of the workforce receiving training.

[16] The QMLE results also indicate negative minimum wage effects only on the percent of support staff and supervisors trained. Moreover, the QMLE magnitudes are nearly identical to those using the Tobit procedure.

References

Acemoglu, Daron and Jorn-Steffen Pischke. 1999. Minimum wages and on-the-job training. *NBER working paper* #7184.

Akerlof, George A. and Janet L. Yellen. 1986. *Efficiency Wage Models of the Labor Market*. Cambridge: Cambridge University Press.

Becker, Gary S. 1964. *Human capital: A theoretical and empirical analysis, with special reference to education*. New York: Columbia University Press.

Greene, William H. 2000. *Econometric Analysis*, fourth edition. New Jersey: Prentice-Hall, Inc.

Grossberg, Adam J. 2000. The effect of formal training on employment duration. *Industrial Relations* 39: 578-99.

Grossberg, Adam J. and Paul Sicilian. 1999. Minimum wages, on-the-job training, and wage growth. *Southern Economic Journal* 65: 539-56.

Hashimoto, Masanori. 1982. Minimum wage effects on training on the job. *American Economic Review* 72: 1070-87.

Hausman, Jerry A. 1978. Specification tests in econometrics. *Econometrica* 46: 1251-71.

Jeong, Jinook and G. S. Maddala. 1993. A perspective on application of bootstrap methods in econometrics. In *Handbook of Statistics*, eds. G. S. Maddala, C. R. Rao, and H. D. Vinod. Amsterdam: Elsevier.

Johnston, Jack and John DiNardo. 1997. *Econometric Methods*, fourth edition. New York: McGraw-Hill Companies, Inc.

Lazear, Edward P. and Frederick H. Miller. 1981. Minimum wage versus minimum compensation. In *Report of the minimum wage study commission*, volume 5. Washington, DC: U.S. Government Printing Office, pp. 347-80.

Leighton, Linda and Jacob Mincer. 1981. The effects of minimum wages on human capital formation. In *The economics of legal minimum wages*, edited by Simon Rottenberg. Washington, DC: American Enterprise Institute, pp. 155-73.

Lynch, Lisa M. and Sandra E. Black. 1998. Beyond the incidence of employer-provided training. *Industrial and Labor Relations Review* 52: 64-81.

Moulton, Brent R. 1986. Random group effects and the precision of regression estimates. *Journal of Econometrics* 32: 385-97.

Murphy, Kevin and Robert Topel. 1985. Estimation and inference in two step econometric models. *Journal of Business and Economic Statistics* 3: 370-79.

Neumark, David and William Wascher. 2001. Minimum wages and training revisited. *Journal of Labor Economics* 19: 563-95.

Newey, Whitney K. 1985. Generalized method of moments specification testing. *Journal of Econometrics* 29: 229-56.

Papke, Lelie E. and Jeffrey M. Wooldridge. 1996. Econometric methods for fractional response variables with and application to 401(k) plan participation rates. *Journal of Applied Econometrics* 11: 619-32.

Prendergast, Canice. 1993. The role of promotion in inducing specific human capital acquisition. *Quarterly Journal of Economics* 108: 523-34.

Rosen, Sherwin. 1972. Learning and experience in the labor market. *Journal of Human Resources* 7: 326-42.

Royalty, Anne Beeson. 1996. The effects of job turnover on the training of men and women. *Industrial and Labor Relation Review* 49: 506-21.

Schiller, Bradley R. 1994. Moving up: The training and wage gains of minimum-wage entrants. *Social Science Quarterly* 75: 622-36.

Tiebout, Charles. 1956. A pure theory of local expenditures. *Journal of Political Economy* 64: 416-24.

TABLE 1

States with Minimum Wages that Exceeded the Federal Minimum Wage

	Minimum Wage in 1996	Weighted Gap
Federal	4.25/4.75	
Alaska	4.75	0.375
Connecticut	4.27	0.000
Delaware	4.65	0.275
District of Columbia	5.25	0.875
Hawaii	5.25	0.875
Iowa	4.65	0.275
New Jersey	5.05	0.675
Oregon	4.75	0.375
Rhode Island	4.45	0.075
Vermont	4.75	0.375
Washington	4.90	0.525

Note – In 1996, the federal minimum wage was not implemented until October 1. All other minimum wages were implemented at the beginning of the calendar year. The minimum wage gaps are calculated using a weighted average of the federal minimum wage (i.e., $4.375).

TABLE 2A

Descriptive Statistics for the Explanatory Variables

Variable	Mean	Std. Dev.
Employment and Sales:		
50-99 employees	0.1430	0.3502
100-249 employees	0.2240	0.4171
250-999 employees	0.3752	0.4844
1,000 or more employees	0.1494	0.3566
multiple estab firm	0.7031	0.4571
employment increased in past 3 years	0.4827	0.4999
employment decreased in past 3 years	0.2140	0.4103
turnover rate	19.0276	185.7143
average number of weeks to fill a position	3.3342	3.0289
natural log of total sales	17.4848	1.7816
Region:		
estab located in west	0.1639	0.3704
estab located in Midwest	0.2996	0.4583
estab located in south	0.3770	0.4849
Workforce Characteristics:		
% 18+ with a high school diploma	31.2046	6.5922
% 18+ with a bachelors degree	12.5718	4.9626
number of permanent part-time workers	25.8315	143.4752
number of temporary workers	18.1521	105.4377
% of female workers	38.5591	23.5415
% of minority workers	25.9598	24.3694
% of front-line workers	58.6984	23.9328
% of support staff workers	12.7694	12.4860
% of technician workers	10.5807	12.9012
% of supervisory workers	7.6821	5.0851
% of non-supervisors unionized	23.2995	37.6262
quality of local high school unacceptable	0.0219	0.1463
quality of local high school barely acceptable	0.1658	0.3720
quality of local high school acceptable	0.5692	0.4954
quality of local high school more than adequate	0.1821	0.3861
quality of local high school outstanding	0.0146	0.1199
Workplace Organization:		
% of non-management in self-managed teams	17.7716	29.5405
% of non-supervisors in job rotation	22.4222	30.6450
Benefits:		
estab contributes to pension or severance	0.8707	0.3357
estab contributes to medical or dental	0.9927	0.0851
estab contributes to child care or family leave	0.7514	0.4324
estab contributes to life insurance	0.9517	0.2144
estab contributes to sick pay or vacation	0.9945	0.0738
Minimum Wage:		
state min wage	4.4115	0.1381
state min wage minus federal min wage	0.0365	0.1381

Note – This table includes all of the explanatory variables in the regressions except the categorical industry and the establishment- and occupation-specific minimum wage variables.

TABLE 2B

Descriptive Statistics for Training and Wage Variables by Occupation

Variable	Mean	Std. Dev.
All		
% of workers receiving training	58.0761	36.9062
average number of hours trained	27.6146	43.8773
average wage	14.1039	4.2221
Front Line		
% of workers receiving training	59.2058	40.8478
average number of hours trained	28.1876	48.9843
average wage	12.7150	7.2125
Support Staff		
% of workers receiving training	54.2217	39.3727
average number of hours trained	20.4044	30.1949
average wage	12.2880	3.5758
Technical		
% of workers receiving training	61.7915	39.5289
average number of hours trained	30.9882	48.9026
average wage	16.0765	4.9419
Supervisory		
% of workers receiving training	65.0735	39.9918
average number of hours trained	27.5455	38.1044
average wage	16.7594	4.8256
Managerial		
% of workers receiving training	59.8867	40.1285
average number of hours trained	27.8470	49.2504
average wage	23.1587	7.8222

TABLE 2C

Descriptive Statistics for Training and Wage Variables by Firm Size

Variable	Mean	Std. Dev.
1-49 employees		
% of workers receiving training	48.8899	42.3634
average number of hours trained	27.2904	72.7526
average wage	14.6345	4.2177
50-99 employees		
% of workers receiving training	44.3509	39.6647
average number of hours trained	18.1832	24.6551
average wage	13.6102	3.6745
100-249 employees		
% of workers receiving training	55.26.53	37.2239
average number of hours trained	25.0227	31.8413
average wage	13.6613	4.3466
250-999 employees		
% of workers receiving training	63.6000	33.9529
average number of hours trained	31.3155	43.2826
average wage	13.7479	3.9130
1,000+ employees		
% of workers receiving training	68.2201	30.6076
average number of hours trained	31.4688	46.3714
average wage	15.7495	4.8356

TABLE 3

The Effect of Minimum Wages on Percent of Workers Trained and Hours of Training Using a State-Level Minimum Wage Measure

Occupational Group:	(1)	(2)
All		
Estimate	-33.2047	-6.4543
Std. Error	(11.9402)	(12.3958)
R-squared	0.4296	0.1924
Front Line		
Estimate	-38.5873	-6.1059
Std. Error	(13.5612)	(14.3963)
R-squared	0.4153	0.1985
Support Staff		
Estimate	-11.3607	-14.5429
Std. Error	(12.1278)	(10.9801)
R-squared	0.4161	0.2447
Technical		
Estimate	-40.0778	-0.0762
Std. Error	(15.2753)	(15.3427)
R-squared	0.3602	0.1691
Supervisory		
Estimate	-19.8936	-9.2563
Std. Error	(13.0260)	(9.0628)
R-squared	0.4138	0.2027
Managerial		
Estimate	-28.6259	-3.6990
Std. Error	(13.2516)	(8.4537)
R-squared	0.3958	0.2288

Note – The dependent variable in (1) is the percent of workers trained. The dependent variable in (2) is the average hours of training per worker. The sample size is 1,098 for all regressions. All equations include the remaining variables in the table of descriptive statistics in addition to 20 industry dummies. Standard errors, which are adjusted for state group effects, are in parentheses.

TABLE 4

Difference-in-Difference Estimates of the Effects of Minimum Wages on the Percent of Workers Trained and Hours of Training

Occupational Group:	(1)	(2)
Front Line		
Estimate	-2.3420	0.2407
Std. Error	(14.9700)	(13.1012)
Support Staff		
Estimate	6.5899	-4.7185
Std. Error	(15.4666)	(9.8664)
Technical		
Estimate	-12.5184	8.7051
Std. Error	(15.4672)	(14.1721)
Supervisory		
Estimate	6.4784	-1.4752
Std. Error	(16.3385)	(9.3511)
R-squared	0.4338	0.2143
Hausman-Wu	0.29	0.50

Note – The dependent variable in (1) is the percent of workers trained in a specific occupational category. The dependent variable in (2) is the average hours of training in a specific occupational category. The base category is managerial workers. All equations include the remaining variables in the table of descriptive statistics in addition to 20 industry dummies and state fixed effects. Standard errors, which are adjusted for group effects, are in parentheses.

TABLE 5

The Effect of Minimum Wages on Percent of Workers Trained and Hours of Training Using Establishment- and Occupation-Level Minimum Wage Measures

Occupational Group:	(1)	(2)
All		
Estimate	-41.0771	10.7036
Std. Error	(22.9898)	(43.4677)
R-squared	0.5336	0.2649
Hausman-Wu	2.01	0.01
Front Line		
Estimate	-7.1464	-19.5497
Std. Error	(16.6077)	(14.8701)
R-squared	0.5390	0.2805
Hausman-Wu	1.68	0.96
Support Staff		
Estimate	-211.4745	10.7424
Std. Error	(58.2997)	(21.3342)
Corrected Std. Error	(77.1454)	
R-squared	0.5197	0.3945
Hausman-Wu	3.63**	0.40
Technical		
Estimate	7.2278	22.7799
Std. Error	(27.0670)	(31.5805)
R-squared	0.4720	0.2253
Hausman-Wu	0.63	1.78
Supervisory		
Estimate	-117.6360	71.2078
Std. Error	(50.4879)	(41.4297)
Corrected Std. Error	(58.8394)	
R-squared	0.5449	0.2848
Hausman-Wu	2.34*	1.37
Managerial		
Estimate	-1.5424	50.9651
Std. Error	(29.6088)	(36.1476)
R-squared	0.5451	0.2806
Hausman-Wu	0.97	0.07

Note – The dependent variable in (1) is the percent of workers trained. The dependent variable in (2) is the average hours of training per worker. All equations include the remaining variables in the table of descriptive statistics in addition to 20 industry dummies and state fixed effects. Standard errors, which are adjusted for state group effects, are in parentheses. An * and ** indicates that the Hausman-Wu test statistic is large enough to reject the null hypothesis of exogeneity at the 5 and 1 percent level of significance, respectively. In those cases, the two-stage results are reported.

TABLE 6

Tobit Difference-in-Difference Estimates of the Effects of Minimum Wages on the Percent of Workers Trained and Hours of Training

Occupational Group:	(1)	(2)
Front Line		
Estimate	-12.5407	0.4814
Std. Error	(39.5420)	(18.7843)
Support Staff		
Estimate	6.4306	-5.7485
Std. Error	(42.4360)	(15.5504)
Technical		
Estimate	-35.4213	10.3315
Std. Error	(43.2113)	(19.2656)
Supervisory		
Estimate	16.1544	-1.6631
Std. Error	(46.4181)	(15.3457)
$\Phi(\hat{t}/\sigma)$	0.7764	0.7224
Wald Chi-squared	605.36	622.63

Note – The dependent variable in (1) is the percent of workers trained in a specific occupational category. The dependent variable in (2) is the average hours of training in a specific occupational category. The base category is managerial workers. All equations include the remaining variables in the table of descriptive statistics in addition to 20 industry dummies and state fixed effects. Standard errors, which are adjusted for group effects, are in parentheses. The degrees of freedom for the Wald Chi-squared statistics are 61 for column (1) and 104 for column (2).

TABLE 7

Tobit Estimates of the Effect of Minimum Wages on Percent of Workers Trained and Hours of Training Using Establishment- and Occupation-Level Minimum Wage Measure

Occupational Group:	(1)	(2)
All		
Estimate	-95.6686	-10.0012
Std. Error	(40.7012)	(61.1640)
Wald Chi-squared	898.99	572.79
$\Phi(\hat{t} / \sigma)$	0.9049	0.7291
N Left-Censored	189	189
N Right-Censored	172	0
Front Line		
Estimate	-24.7889	-26.5001
Std. Error	(38.1088)	(20.8376)
Wald Chi-squared	369.25	694.70
$\Phi(\hat{t} / \sigma)$	0.8289	0.7357
N Left-Censored	189	189
N Right-Censored	423	0
Support Staff		
Estimate	-531.5070	11.1665
Std. Error	(133.4764)	(29.3706)
Corrected Std. Error	(174.2821)	
Wald Chi-squared	466.90	2528.92
$\Phi(\hat{t} / \sigma)$	0.8238	0.7157
N Left-Censored	189	189
N Right-Censored	340	0
Technical		
Estimate	-34.7793	32.1258
Std. Error	(90.7214)	(43.1963)
Wald Chi-squared	22.84	193.62
$\Phi(\hat{t} / \sigma)$	0.7324	0.7054
N Left-Censored	189	189
N Right-Censored	430	0
Supervisory		
Estimate	-281.2885	94.8657
Std. Error	(141.6928)	(53.5086)
Corrected Std. Error	(180.6712)	
Wald Chi-squared	257.30	357.38
$\Phi(\hat{t} / \sigma)$	0.8106	0.7486
N Left-Censored	189	189
N Right-Censored	491	0
Managerial		
Estimate	-36.1474	45.3279
Std. Error	(121.9013)	(44.2573)
Wald Chi-squared	223.60	196.23
$\Phi(\hat{t} / \sigma)$	0.8289	0.7454
N Left-Censored	189	189

N Right-Censored	399	0

Note – The dependent variable in (1) is the percent of workers trained. The dependent variable in (2) is the average hours of training. All equations include the remaining variables in the table of descriptive statistics in addition to 20 industry dummies and state fixed effects. Standard errors, which are adjusted for state group effects, are in parentheses. The degrees of freedom for the Wald Chi-squared statistics are 54 for column (1) and 95 for column (2).

APPENDIX A

OLS Coefficient Estimates for "Percent Trained" Regression of Equation (3)

Variable	Estimate	Std. Error
Employment and Sales:		
50-99 employees	-1.5261	2.7524
100-249 employees	-0.0845	2.8994
250-999 employees	0.7913	3.2128
1,000 or more employees	11.3054	3.7528
multiple estab firm	6.7397	2.0466
employment increased in past 3 years	3.4842	1.9556
employment decreased in past 3 years	8.3347	3.1884
turnover rate	-0.1212	0.0423
Workforce Characteristics:		
% 18+ with a high school diploma	1.8782	0.3428
% 18+ with a bachelors degree	1.1346	0.3512
number of permanent part-time workers	-0.0244	0.0025
number of temporary workers	0.0047	0.0087
% of female workers	0.1829	0.0561
% of minority workers	-0.0350	0.0498
% of front-line workers	0.1094	0.1129
% of support staff workers	0.2222	0.1397
% of technician workers	0.1455	0.1272
% of supervisory workers	-0.1280	0.2258
quality of local high school unacceptable	-9.6451	7.4622
quality of local high school barely acceptable	26.5028	4.6127
quality of local high school acceptable	10.7400	3.9521
quality of local high school more than adequate	12.2541	4.1207
quality of local high school outstanding	-2.4334	6.4764
Workplace Organization:		
% of non-management in self-managed teams	0.2791	0.0315
% of non-supervisors in job rotation	0.0400	0.0346
Benefits:		
estab contributes to pension or severance	6.8975	2.4343
estab contributes to medical or dental	-32.4541	11.9500
estab contributes to child care or family leave	13.6998	2.1177
estab contributes to life insurance	5.5753	4.3566
estab contributes to sick pay or vacation	-4.8653	7.4043
Occupation Dummies:		
front line	0.4813	3.7696
support staff	-5.1791	3.2538
technical	9.4531	4.1630
supervisory	3.0989	3.7876

Note – This table excludes industry and state dummies.