Disabled Workers and Earnings Losses: Some Evidence from Workers with Occupational Injuries

Michele Campolieti and Harry Krashinsky*

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Abstract

We examine the effects of work-related disabilities on the earnings losses of disabled male workers. First, we analyze the extent of the wage losses of disabled workers who remain at their pre-injury job relative to disabled workers who leave their pre-injury job, using regression and bias reduced matching estimators. Second, we estimate a components-of-variance model that examines the persistence of earnings shocks for disabled workers. Our estimates suggest that disabled male workers with work-related injuries who do not return to work with their accident employer have much larger wage losses and more persistent earnings shocks.

*Both authors are affiliated with the Division of Management, University of Toronto at Scarborough and Centre for Industrial Relations, University of Toronto. Both authors gratefully acknowledge the financial support of the Social Sciences and Humanities Research Council of Canada. The matching estimates were obtained using the STATA ado files created by A. Abadie, D. Drucker, J.L. Herr and G.W. Imbens. Please address correspondence to: Harry Krashinsky; Centre for Industrial Relations; University of Toronto; 121 St. George Street; Toronto, Ontario; M5S 2E8; email: harry.krashinsky@utoronto.ca.

1 Introduction

A well-documented finding in the empirical literature on labor market earnings is that bad health is associated with lower earnings. Many studies have attempted to explain this finding with cross-sectional data on physical and mental health measures, such as alcohol usage, body mass index, the presence of mental illness, and overall self-reported health levels. In addition to these measures, a popular approach for considering the impact of health on wages has been to examine the relationship between earnings and physical or mental limitations for workers due to disabilities. The popularity of this approach is due to the fact that many researchers view a decrease in health as a loss in overall earnings capacity because of a loss in general human capital, and the limitations caused by disabilities are well-suited to this framework.

In this paper, we consider this human capital explanation for the wage dynamics of disabled male workers by using a unique Canadian data set on workers who suffer injuries at work. This data contains administrative information on the nature of a worker's injury as well as his hourly earnings before and after his injury to determine the impact of several factors on a worker's decline in wages. This data is quite useful because it allows us to make a number of contributions to the literature. First, because it contains information about workers who suffer accidents at work and are disabled as a result, the impact of these disabilities is unforeseen. Other data sources contain information on disabilities suffered by workers but not all of which are unforeseen. For example, many degenerative diseases that result in disabilities are often included in other studies, which makes it difficult to infer the impact of a disability on wages because a worker can take measures once a degenerative illness is diagnosed to adjust to its impact on his or her earnings and lifestyle. Second, the data contains workers identified as disabled by adjudicators from the Workers' Compensation Board of Ontario instead of self-reports on disability. Self-reported data can be biased because some individuals may describe themselves as disabled in order to justify weak labor market attachment and this can impact inferences made about the effect of a disability on labor market outcomes. Third, because this data contains information about the worker's injury it is possible to address the issue of how the severity of the injury impacts labor market outcomes. This is not possible in widely available labor market data sets. Fourth, because this data contains information on pre- and post-injury earnings, it will be possible to analyze the impact of disabling injuries on wages in a dynamic context.

We focus on two issues. First, we examine the short-term effects of a disabling work-related injury by comparing the wage losses of disabled workers who return to work with their accident employer with those that do not. Using our data we determine whether the immediate drop in a worker's earnings after a disabling injury is due to the destruction of general human capital or from the benefits of remaining at the pre-injury employer. This is an issue that has not been explored before in the literature examining the wage dynamics of disabled workers. We obtain these estimates using regression and matching estimators. Second, we also explore the longer-term effects of a disability on wages using a components-of-variance model that allows us to examine the persistence of earnings shocks.

Our principal findings suggest that disabled male workers who return to their pre-accident employers have relatively small wage losses and injury severity is not a significant determinant of wage losses for these workers. Moreover, our estimates indicate that workers who return to their pre-accident employer earn 27 percent more than those that leave the pre-accident employer after their injury. We also consider the effect of other worker characteristics on wage losses and find that older and younger workers do not differ in terms of their wage losses, but those for unionized and non-unionized workers can differ a great deal. We argue that these findings are consistent with a loss in firm-specific human capital, so that these workers are most affected by their ability to return to their time-of-accident firm and not by their loss in earnings capacity. Our estimates from the components-of-variance model suggest that males who do not return to their time of accident employer can have much more persistent earnings shocks than those who initially return to the accident employer.

2 Literature Review

The literature relating health to labor market outcomes originates with Becker's (1964) discussion of human capital and health capital, in which he argued that the motivation for investments in general human capital, such as education, was similar to the rationale for investing in health capital. Grossman (1972) formalized this idea with a model in which health directly impacted consumption and labor market outcomes. An empirical investigation of these ideas was predicated on the notion that the destruction of a worker's human capital caused by a disability should be directly evident in a worker's labor market outcomes, such as earnings. A detailed discussion of this literature, which has almost exclusively analyzed cross-sectional data, can be found in Currie and Madrian (1999).

A few papers in the existing literature have conducted analyses of the impacts of disability on earnings with longitudinal data. Boden and Galizzi (2003) study the relative labor market performance of male and female workers before and after suffering a disabling work-related injury. They found that although women and men exhibit similar earnings losses in the quarter after they are injured, women tend to fare worse than men in the years following the injury. Although male earnings exhibit a modest recovery during this period, female earnings recover more slowly, which the authors take as being consistent with discriminatory behavior against women.

Charles (2003) considers the effect of disability on worker behavior over time using a human capital framework which incorporates health capital and observes that if a disability diminishes the healthy capital that the worker has amassed then there are a few implications that should be observed in the data. First, the greater the severity of the disability, the larger the damage to the healthy capital and, consequently, the greater the wage loss. Second, older workers should exhibit greater wage losses immediately after the onset of a disability because older workers have more healthy capital to be eliminated by a disability. Third, younger workers should exhibit larger growth in post-disability earnings because they have a greater incentive to invest in disability capital to assist them in their new state of health. Since Charles (2003) uses the PSID, his sample of workers report whether they are disabled, but not the severity or type of disability from which they suffer. As a result, he measures the "chronicity" of the disability, which is equal to the number of periods the worker reported being disabled. With this measure he finds that greater chronicity is associated with larger wage losses. He also finds younger workers with disabilities also exhibit smaller wage losses and more robust wage gains. All these findings are consistent with the human capital model he proposes.

A limitation of the papers in the existing literature examining the impact of disabilities on earnings is that virtually all of them rely on self-reports to identify disabled workers. This means that if a worker identifies himself as "disabled" to justify weak labor market attachment they will be included in a study. Another limitation is that some of the disabilities that can afflict a worker are foreseeable, so it is possible that individuals may react in advance of being disabled (or reporting that they are disabled). Either of these issues can influence estimates of the impact of a disability on earnings. However, administrative data, which is employed in this paper, reports disability assessments based on medical reports regarding the nature and severity of the disability and can circumvent such problems. In addition, because our data set is composed entirely of workers who suffer work-related accidents, none of the workers in our sample are afflicted by foreseeable disabilities.

3 Data

To consider the wage dynamics of disabled workers, we use data from the Survey of Ontario Workers with Permanent Impairments (SOWPI), which was collected by the Workers' Compensation Board of Ontario, Canada. The SOWPI is a survey of permanently disabled workers who received a physical exam from the Ontario Workers' Compensation Board (WCB) between June 12, 1989 and August 31, 1990. In Ontario, workers who never fully recover from their injury and suffer some loss in their capacity to earn are called permanently disabled. These workers had all, in the opinion of their physician and WCB claim adjudicator, reached the point of maximum medical improvement. In other words, the medical condition of these claimants had stabilized.

The results from the worker's physical exam would be used to assign them a disability rating, which would be used to compute their permanent disability benefits.[1]

In addition to demographic information about the workers and some information about their employers, the survey collected information on the pre- and post-injury employment experiences of permanently disabled workers. For example, the survey contains information about whether the worker returned to work with the time-of-accident employer or a new employer, the wages earned at the post-injury jobs as well as the number of hours worked. These are retrospective reports of the worker's employment history, which contain information on as many as four jobs after the injury as well as their pre-injury job. Unfortunately, the information on the post-injury jobs does not contain union status, industry, occupation or firm size – but this information is available for the time-of-accident employer. The survey data also includes some information from the Ontario WCB's administrative records on the nature of the worker's injury and the body part that was injured.

As we noted earlier, the results of the worker's physical exam would be used to determine the worker's disability rating, which represents the worker's loss in functional capacity. The disability rating can be used as a proxy for the severity of the injury. For example, a disability rating of 25 percent means that the worker has lost 25 percent of their earnings capacity. Unfortunately, the SOWPI does not contain the respondent's actual disability rating, but it does contain detailed information on the nature of a worker's injury, so we used this information to create an estimate of the disability rating. Specifically, we used the regression results in Hyatt (1996), which related actual disability ratings from the Ontario Workers' Compensation Board's administrative records to worker characteristics and injury classifications based on ICD9 diagnosis codes.[2] The coefficient estimates from Hyatt's regression were used to create the expected disability rating.

We use the information in the survey to create two data sets. First, we take infor-

[1] Internal assessments of the SOWPI by WCB personnel indicated that the data was representative of the population of permanent disability claimants in Ontario.

[2] In his work, Hyatt (1996) used data on 34,032 claims, between 1984 and 1989, to estimate his regression.

mation on a worker's pre-injury job as well as their first post-injury job to examine the short-term loss in wages these workers experience. We can only estimate this regression for workers who return to work. We include male workers aged 20 to 64 who had accidents between 1979 to 1989, which produces a sample of 4,171 males with pre- and post-injury information. Second, we also used the retrospective reports for their pre- and (a number of) post-injury jobs to create a panel data set. We will use this second data set to obtain estimates of the persistence in wages experienced by workers after their injury to examine the longer-term consequences of a disability on wages. This data set used the worker's pre-injury job plus three post-injury jobs, which covered about four to six years of calendar time. We also restrict this sample to males between the ages of 20 and 64, but only those who had accidents between 1979 and 1984, and have 710 males in this data set. This data set only contains workers who switched jobs, so it is a subsample of the data set with the pre-injury and first post-injury jobs. With both data sets we consider two subsamples: (i) workers who initially returned to work with their pre-injury employer and then leave for other jobs; and, (ii) workers who did not ever return to work with their pre-injury employer after they re-entered the labor market. This comparison has not been considered before in the literature and may be a potentially important for understanding the wage dynamics of disabled workers.

Descriptive statistics for the first data set we described are presented in Table 1 for the pooled sample as well as the samples of workers that returned and did not return to work with the accident employer. Sample means in the first column indicate that most men in the pooled sample return to their pre-injury employer and lose about 5 percent of their wages after an injury. The age distribution is almost evenly split between older and younger men, but the majority of these men have low levels of educational attainment. This is primarily due to the fact that most work-related injuries occur in blue-collar jobs and workers in these jobs tend to have lower levels of education. The expected disability rating for the sample is 0.11, implying that the average worker in the sample has lost 11 percent of his earnings capacity.

An interesting fact is revealed when the sample is split into the group of workers who do return to their pre-injury employer and those that do not: both groups have similar expected disability ratings, but the wage losses after their injuries are very different. Workers who return to their pre-injury employer report minor wage losses of just over 1 percent on average, but workers who do not return to their pre-injury employers report wage losses of approximately 25 percent. This striking difference in wages does not appear to arise from major differences in other observable variables, such as age or education. This would suggest that returning to one's pre-injury employer or issues stemming from firm-specific benefits are quite important for determining the wage dynamics of disabled workers.

4 Empirical Models

4.1 Regression Analyses

A simple approach for considering the relative impact of not returning to the pre-injury employer can be achieved by examining the wages of the disabled workers using the following regression

$$\begin{aligned} \log w_{it} &= \beta_0 + \beta_1 Accemp_{it} + \beta_2 PostInjury_{it} + \beta_3 PostInjury_{it} * Accemp_{it} \\ &\quad + X_{it}'\gamma + u_{it}, \end{aligned} \tag{1}$$

where w_{it} is the real hourly wage, $Accemp_{it}$ is a dummy variable equal to 1 if the worker is employed by the pre-accident employer, $PostInjury_{it}$ is a dummy variable that takes the value 1 for the post-injury observation, $PostInjury_{it} * Accemp_{it}$ is an interaction term between $Accemp_{it}$ and $PostInjury_{it}$, and the vector X contains controls for observable characteristics. This regression is estimated using data from the pre-injury job as well as the first post-injury job. The estimate on the interaction term will capture the "wage premium" for disabled workers that return to work with their pre-injury employers, relative to those that leave, after their injury. However, this is a naive estimator because it ignores any potential biases due to selection effects for workers who do and do not return to their pre-injury employer. To address these selection effects, we use matching estimators to compare similar individuals (based on observable characteristics) in these two groups of workers.

4.2 Matching Analyses

We also obtain estimates of the effect of remaining with the pre-injury employer using a matching estimator. We provide a brief description of the estimator, the details can be found in Abadie and Imbens (2002). Let the observed outcome (the change in log wages), Y_i, be such that

$$Y_i = Y_i(T_i) = \begin{cases} Y_i(0) & \text{if } T_i = 0 \\ Y_i(1) & \text{if } T_i = 1 \end{cases}, \tag{2}$$

where $T_i = 1$ if the individual received the treatment (which, in our case, is returning to the accident employer) and 0 otherwise, and only one of the potential outcomes, i.e., either $Y_i(0)$ or $Y_i(1)$, is observed. The matching estimator considered by Abadie and Imbens (2002) imputes the missing potential outcome by using average outcomes for individuals with similar values for the explanatory variables.

Abadie and Imbens (2002) show that a simple matching estimator will be biased in finite samples if the matching is not exact. Consequently, they propose a bias-corrected matching estimator, which adjusts the difference within the matches for the differences in the covariates, to remove some of the bias. The adjustment is based on two regression functions. To estimate the average treatment effect, the regressions can be estimated using data from the matched sample only. After the estimates of the regression functions are obtained, the missing potential outcomes can be written as $\widetilde{Y}_i(0)$ and $\widetilde{Y}_i(1)$. The sample average treatment effect can then be computed as

$$\widehat{\tau}_M = \frac{1}{N} \sum_{i=1}^{N} \left(\widetilde{Y}_i(1) - \widetilde{Y}_i(0) \right). \tag{3}$$

The estimates from the bias-corrected matching approach can be compared with the regression estimates to determine the potential impact of a selection bias on the estimates.

4.3 Components-of-Variance Model

The regression and matching approaches that we discussed are appropriate for analyzing short-term wage losses for disabled workers, but we are also interested in the long-term impacts of a disability on wages for job-changers. To explore this issue, we estimate a components-of-variance model that can be used to examine the persistence of wage shocks. We assume that the log wage of individual i in period t is given by

$$\log w_{it} = \omega_i + v_t + u_{it} + \mu_{it}, \tag{4}$$

where $u_{it} = \alpha u_{it-1} + \zeta_{it}, var(\zeta_{it}) = \sigma_t^2$ for $t = 1, 2, ..., T, cov(\zeta_{it}, \zeta_{is}) = 0$, for $t \neq s, var(\omega_i) = \sigma_\omega^2, var(\mu_{it}) = \sigma_\mu^2, cov(\zeta_{it}, \omega_i) = cov(\zeta_{it}, \mu_{it}) = cov(\omega_i, \mu_{it}) = 0$.

The model presented in equation (4) represents earnings as a person-specific constant, ω_i, an aggregate effect, v_t, as well as person- and period-specific wage shocks, which are comprised of two components. The first is a serially correlated (first-order) component with a time-varying variance, u_{it}. The other portion is a serially uncorrelated component, μ_{it}, which can be interpreted as white-noise measurement error. The estimates of α from the autoregressive component can be used to infer the long-term impact of an earnings shock on a disabled worker's wages.

The components-of-variance model is estimated using a minimum distance estimator, which requires using equation (4) to create theoretical expressions for the variance and covariances of wages. These moment conditions, which use the variance of $\log w_{it}$ and covariances between $\log w_{it}$ and lagged values of $\log w_{it}$, are presented in Table A1.[3] The parameters of interest from this model are estimated by minimizing the following quadratic form

$$(m - f(\Xi))' W^{-1} (m - f(\Xi)), \tag{5}$$

where m is a vector of sample moments, $f(\Xi)$ is a vector of the theoretical moment conditions (from Table A1) and W^{-1} is a weighting matrix. We use the identity matrix as the weighting matrix, which produces the equally weighted minimum distance estimator (EWMD). We employ the EWMD rather than the optimal minimum distance

[3]To obtain estimates of our components-of-variance model it was necessary to use all of the respondent's retrospective reports on the jobs we included in the panel data set in order to construct the sample moments of earnings. For instance, if a worker began his first post-injury job in 1980 and moved to his second post-injury job in 1982, then this would allow us to construct a two-year covariance for the worker. The vast majority of the workers in our sample had yearly job changes so it was possible to obtain good estimates of the first-, second- and third-order covariances for wages.

estimator, which uses the second moment matrix of the vector m as the weighting matrix, because it has been found to produce more stable estimates and have better small sample properties (Altonji and Segal (1996)). This is the approach that has been taken by recent papers examining the covariance structure of earnings (e.g., Baker (1997) and Baker and Solon (2003)). We also compute a goodness of fit test statistic suggested by Newey (1985) for each of the models we estimated.

5 Empirical Results

Prior to presenting our results for the estimates of the effects of remaining at the pre-injury employer on wages we further examine some of the issues we highlighted in the data section on the relationship between some individual characteristics and the wage losses of these disabled workers. We regressed the change (i.e., post-injury minus pre-injury) in the log of real wages for workers on the expected disability rating, controls for age, educational attainment, pre-injury union status as well as industry and present the estimates in Table 2. The estimates in the first column of Table 2 demonstrate that in the pooled sample, the disability rating is a highly significant determinant of the loss in earnings. This is consistent with the well-established notion that health capital is much like human capital and that an increase in the severity of the injury suffered by the worker should result in larger wage losses for that worker. However, we do not find a statistically significant relationship between age and the change in wages. Likewise, most of the education dummies - with the exception of the dummy for a university degree - are not statistically significant determinants of the loss in earnings. Another important point that is echoed from Table 1 arises in column (2) of Table 2; an indicator variable for whether or not the worker returned to his pre-accident employer is highly significant.

We also estimated the regressions splitting the sample into the groups that do and do not return to their pre-accident employer. For the subsample of workers who do return to their accident employer (see column (3)), the disability rating, which is a proxy for severity, is not a significant determinant of the individual's change in wages.

This is an interesting contrast to the results in the first two columns of this table, since it suggests that the destruction of general human capital through a disabling injury need not be a significant determinant of wages if the worker remains at his pre-injury firm. More importantly, since a large majority of the sample does return to their pre-injury employer, this suggests that the finding that an increase in the severity of the disability impacts earnings is due to only a subsample of workers who do not return to their pre-injury firms. This is consistent with the worker being insured by the firm through a long-term contract. In particular, Abowd and Card (1987) distinguish between two different kinds of employment contracts: contracts in which the worker is paid his or her marginal product by the firm (the labor supply model); and, contracts in which the firm pays the worker an amount that does not fluctuate with changes in productivity (a long-term contracting model). The difference between the two models is that changes in productivity should be most evident in wage changes for the labor supply model, but relatively modest for the long-term contracting model. The estimates in Table 2 suggests that workers who remain at their pre-injury employer are paid wages that are insulated against a negative shock to their health capital (and hence productivity), but workers who leave their pre-injury firm lose this insurance and have their wage significantly impacted by their loss in productivity.[4]

The estimates in Table 2 also indicate that most of the age and educational attainment dummies are not significant determinants of the change in wages for this group. Only the industry dummies, which are not presented in Table 2, and pre-accident union status are significant determinants of the change in wages for this group. These findings can be interpreted as suggesting that firm-specific factors are determining how these workers fare after their injuries. The significantly positive impact of pre-injury union status suggests that a worker who can benefit from institutional protection after his injury can still receive generally equivalent wages after his injury.

For workers who do not return to their pre-accident employer, the regression results are somewhat different. As we noted earlier, column (4) of Table 2 demonstrates that

[4]These estimates are also consistent with those in Campolieti and Krashinsky (2004) who also found support for the intertemporal contracting model.

the severity of the injury is a significant determinant of the wage loss for workers who do not return to their pre-accident employer, which suggests that these workers lose any implicit insurance provided by the firm through a long-term contract. The estimates also indicate that neither age nor education – with the exception of a university degree – has a significant impact on the change in wages, but the pre-injury industry dummies are significant determinants of a worker's wage change.

The results in Table 2 demonstrate that "typical" human capital variables, such as age and education, are (for the most part) not significant determinants of the change in wages, but the loss of important institutional factors can be significant for these workers. For instance, a worker who loses his union status is losing the benefit of his seniority at the firm and there also appears to be firm-specific insurance that some workers lose if they leave their pre-injury employer. A standard (labor supply) model would imply that a worker is paid his marginal productivity and so a new post-injury employer is simply paying the worker his marginal product. Consequently, the disability rating should be a significant correlate of the change in wages because it represents the individual's loss in productivity. However, men who can return to their pre-injury employers and maintain their firm-specific capital (even in the face of large decreases in general human capital) do not have significant wage decreases. This runs contrary to the view that the destruction of human capital due to the disability must cause lower wages for workers in all cases.

5.1 Regression Analysis Estimates of Wage Losses for Disabled Workers

The estimates of the log wage regression in equation (1) are presented in Table 3 for the pooled sample and a series of subsamples. The estimates for the pooled samples are displayed in the first two columns of the table. In the first column, our regression includes only the accident employer dummy, the post-injury dummy and the interaction term between these two dummies. The specification in column (2) includes the two dummies and the interaction term from the first specification as well as a set of control variables (dummy variables for educational attainment, age and location).[5] The estimates in the first two columns demonstrate that the main results for the pooled sample are unchanged by the inclusion of other covariates in the regression; the post-injury dummy variable is associated with a 22.4 percent decline in wages $(\exp(-0.254) - 1)$, which indicates that post-injury wages will be smaller. More importantly, the interaction term between $PostInjury$ and the accident employer dummy variable indicates that post-injury wages are higher for workers who remain at the accident employer, relative to those that leave, after their injury. This estimate is also quite large, suggesting a difference of about 27.3 percent $(\exp(0.241) - 1)$.

To further explore this point, we also consider several different subsamples within the pooled sample to determine whether or not the value of remaining at the pre-accident employer varies for different groups and if these differences provide evidence for the impact of lost human capital on the wage dynamics of disabled workers. In the third and fourth columns of Table 3, we re-estimate the model for workers between the ages of 20 and 39 ("young" workers) and workers between the ages of 40 and 64 ("old" workers). If a disabling injury destroys more human capital for an older worker, there should be larger wage losses for older workers and a greater drop in the wage rate for older workers leaving the firm. However, the results in columns (3) and (4) suggest this is not the case. The estimate on the interaction term for older workers remaining with the firm (approximately 26 percent, $\exp(0.233) - 1$) is about the same as the estimate for younger workers (about 28 percent, $\exp(0.245) - 1$). More surprisingly, the estimate for older workers is not significantly different from the estimate for younger workers.

A similar finding is evident in the fifth, sixth and seventh columns of Table 3, which estimate the regressions on groups with different education levels. In all three columns, there is no discernible pattern in the estimates on the interaction term for workers with less than a high-school diploma, high school graduates, or workers with some post-secondary education. The results tend to run counter to the hypothesis

[5] We did not include union status or industry dummies in these regressions because they are only available for the pre-injury data. Similarly, the expected disability rating is only available for the post-injury data.

that wage losses should be greater for workers with larger amounts of general human capital. But this does suggest that firm-specific human capital may be an important factor in this analysis and in a very particular way. Although there is a large penalty to leaving the firm after suffering a disabling injury, it does not differ between older and younger workers. This, in turn, implies that if the large penalty is due to losing firm-specific human capital, then this capital is amassed quickly by workers and does not increase during their tenure at the firm.

We also estimate the regression for workers who are members of unions with those that are not and present the estimates in columns (8) and (9) of Table 3. The estimates in column (8) suggest that non-unionized workers who remain with their time-of-accident employers earn 16 percent ($\exp(0.15) - 1$) more than non-union workers who leave their non-union employer after their injury, but this estimate is 49 percent ($\exp(0.40) - 1$) for unionized workers. This is consistent with the loss of an institutional benefit at the firm level for the unionized workers that is not lost for non-unionized workers (who never had these benefits). This is also supportive of the hypothesis that the reason disabled workers exhibit large wage losses after their injuries is not because of the destruction of general human capital by the injury, but rather the destruction of firm-specific benefits, such as seniority at the firm. These institutional benefits are destroyed because the disabled worker moves to a new employer when they re-enter the labor market. More importantly, the magnitude and the relative difference in the estimates between unionized and non-unionized workers is much larger than the average wage loss for the entire sample, which was calculated as 5 percent in Table 1.

5.2 Matching Analysis Estimates of Wage Losses of Disabled Workers

Table 4 presents the sample average treatment effects (SATEs), which were obtained using the code developed by Abadie et al. (2001), from bias-reduced matching estimators for the difference in real log wages for workers remaining and leaving the time-of-accident employer. The advantage of the matching estimator over a regression analysis is that it matches individuals from two groups who are similar on the basis of predetermined observable characteristics. The matching process is particularly useful for our study because we can consider many dimensions to match similar workers who do and do not leave their pre-injury firms after their disabling accidents. To operationalize this approach, we present three sets of estimates that differ in terms of the variables used to find the matches. The first column matches individuals in both groups based on their pre-injury wages and expected disability ratings. These are important variables for a match procedure because using the pre-injury wage will pair individuals with similar levels of pre-disability productivity and, more importantly, the expected disability rating will allow us to compare workers who suffer injuries of a similar severity. The second and third columns of Table 4 allow for a further refinement of the matching process by using more variables to match the workers. The second column creates matches based on the pre-injury wage, the expected disability rating, age and educational attainment, while the third column includes all the variables in the second column as well as dummy variables for location. The location dummies could be important because of differences in urban and rural jobs, especially if there is a wage differential between these regions or if productivity is rewarded differently across regions. The outcome measure of interest in the matching analysis is the difference between pre- and post-injury log of real wages. The treatment variable is the dummy variable indicating whether the worker returned to work with the accident employer.

The estimates in the first row of Table 4 suggest the SATEs on the difference in log wages are about 0.30 for the pooled sample, which are slightly larger, but generally in line with the regression estimates. All of these estimates are statistically different from zero at conventional significance levels and are not overly sensitive to the variables included in the list of variables used to create the matches. The second and third rows demonstrate that the estimates of the wage premium for workers who remain with their firm are about the same, regardless of whether or not they are young or old, which corresponds with the regression results in Table 3. A more interesting result is found in rows three through five, where the impact of remaining with the firm is found to increase with the educational attainment of the worker. This differs from the findings in Table 3, which did not exhibit such a pattern. This suggests that there may be selection issues for more educated workers that are impacting the regression estimates in Table 3. They also suggest that the advantage of remaining at the pre-injury firm stems from maintaining firm-specific capital and this benefit does appear to increase with education. The last two rows of Table 4 confirm what was established in the regression results: remaining with the pre-injury employer is enormously more beneficial for union workers. This suggests that the loss of firm-specific factors (like union seniority) are very important in determining the wage losses of disabled workers.

5.3 Components-of-Variance Estimates

We investigate the longer-term impacts of a disability on wages with the components-of-variance model and present the estimates in Table 5. As we noted in the data section, we estimate this model with three subsamples of data: the pooled sample; the subsample of workers who initially returned to work with their time-of-injury employer but then left the employer for another job; and, the subsample that includes workers who did not return to work with their time-of-injury employer and worked for other employers. The goodness of fit statistics for each model are presented in the last row of Table 5 and are all quite large with very small p-values.

Our estimate for α, which captures the degree of persistence in the data, for the pooled sample is about 0.64 and statistically different from zero. When we restrict the sample to workers that initially returned to work with pre-injury employer the estimate of α is slightly smaller, 0.60. On the other hand, when we estimate the model on the sample of workers that never returned to work with the time-of-accident employer the estimate of α is much larger, about 0.95. This suggests that there is much greater persistence in the earnings of the workers that never return to work with their time-of-accident employers. This is illustrated in Figure 1. There is a substantial drop in wages for workers who leave their employer right after their injury, but not for those that remain. Overall, the change in log wages of disabled workers who initially remain at their time-of-accident after their injury is much smaller than that for workers who do not return to their time-of-accident employer.

To examine the implications of the persistence we considered the effect of a 1-unit innovation in the person-specific component of wages on the discounted average of expected future wages $(1-\beta)\sum_{j=0}^{\infty}\beta^j \log w_{it+j.}$ If the white-noise component of variance is due to measurement error, an innovation in wages is an innovation in the first-order autoregressive component. This means that the effect of 1-unit innovation in current wages on the discounted average of future wages is $\frac{1-\beta}{1-\alpha\beta}$. If we assume that $\beta = 0.926$ (i.e., a discount rate of 8 percent), this will equal 0.167 for the workers that return to the time-of-accident employer and then switch employers. However, for the workers that never return to their time of accident employer it takes a value of 0.592. The first estimate implies that a 10 percent decrease in current wages decreases the discounted average of future wages by 1.7 percent. The second estimate implies a much larger effect. In particular, a 10 percent decrease in current wages decreases the discounted average of future wages by 5.9 percent.

6 Concluding Remarks

We used data on workers who suffer work-related accidents (which are not foreseeable) that result in permanent impairments to examine the wage dynamics of disabled male workers. We examine both the short- and long-term effects of a disability on hourly earnings. Our main finding is that there are distinctly different earnings dynamics for disabled workers who return to work with their accident employer compared to those who do not return to work with their accident employer.

Examining short-term wage losses with a regression based approach we found that typical human capital regressors generally do not have a significant impact on the change in earnings exhibited by workers who are disabled, but other variables are extremely important in this framework. Specifically, union coverage on the pre-injury job and whether or not the worker remains at his pre-injury firm were highly significant determinants of wage losses; even more so than the severity of a worker's injury. In fact, a worker's short-term wage dynamics are drastically different depending on whether or not he remains at his time-of-accident employer. We found that the severity of a worker's injury is not a significant determinant of a worker's wage loss if he remains at his pre-accident firm; despite large decreases in human capital as a result of a disabling injury, these workers do not exhibit large wage losses. In particular, our estimates indicate that workers who remain at their pre-injury firm earn 27 percent more than workers who leave their time-of-accident firms after their injury. We also estimated these regressions on different subsamples and found that this difference is basically the same across different age and educational groups, but very different between union and non-union workers. These findings suggest that the biggest impact of a disability on earnings occurs through the loss of firm-specific benefits, such as a long-term contract, that protects workers against negative health shocks or losses in firm-specific human capital. When we use a matching estimator to examine the loss in wages we find that our results are generally similar to our regression estimates, but that the benefit to remaining at the time-of-accident firm is greater for more educated workers.

We examined the longer-term consequences of a disability on hourly earnings with a components-of-variance model, based on panel data we constructed on workers who have multiple changes in jobs. These estimates also indicate that the effect of a disability on hourly earnings depends on whether the worker returns to their accident employer. In particular, an earnings shock will have much more persistence in the hourly earnings of disabled males who never return to work with their accident employer after they recover from their injury.

Overall, the evidence we present documents an important aspect of earnings dynamics for disabled males that has not been discussed before in the literature. Specifically, disabled males have much smaller losses in wages if they are able to maintain their employment with their pre-disability firms.

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Table 1: Descriptive Statistics

	Pooled Sample	Did Return to Pre-injury employer	Did Not Return to Pre-injury employer
Returned to work at Accident Employer	0.856 (0.351)	--	--
Real Pre-Injury Wage	$9.90 ($3.27)	$10.07 ($3.17)	$8.88 ($3.66)
Log difference post- and pre-injury wage	-0.048 (0.279)	-0.013 (0.169)	-0.256 (0.565)
Expected Disability Rating	0.109 (0.045)	0.108 (0.045)	0.113 (0.043)
Age 20-29	0.181 (0.385)	0.164 (0.371)	0.284 (0.451)
Age 30-39	0.276 (0.447)	0.270 (0.444)	0.312 (0.464)
Age 40-49	0.228 (0.420)	0.238 (0.426)	0.170 (0.376)
Age 50-59	0.179 (0.383)	0.189 (0.392)	0.115 (0.320)
Age 60-64	0.035 (0.183)	0.039 (0.195)	0.007 (0.082)
No Schooling	0.003 (0.058)	0.004 (0.063)	--
Elementary	0.232 (0.422)	0.233 (0.423)	0.228 (0.420)
Some High School	0.406 (0.491)	0.401 (0.490)	0.438 (0.497)
High School Graduate	0.234 (0.423)	0.241 (0.428)	0.191 (0.393)
Some Post-Secondary	0.064 (0.245)	0.061 (0.239)	0.084 (0.278)
University Graduate	0.060 (0.237)	0.060 (0.238)	0.059 (0.236)
Number of Individuals	4,136	3,544	592

Notes: The sample consists of male workers from the SOWPI, aged 20-64, who suffer a permanently disabling injury at work.

Table 2: Wage Change Regressions from Pre- and Post-Injury Wages

	Pooled Sample		Did Return to Pre-injury employer	Did Not Return to Pre-injury employer
	(1)	(2)	(3)	(4)
Disability Rating	0.331 (0.120)	0.284 (0.116)	0.061 (0.087)	1.607 (0.698)
[Age 20-29]				
Age 30-39	-0.030 (0.017)	-0.041 (0.016)	-0.028 (0.012)	-0.106 (0.072)
Age 40-49	0.004 (0.016)	-0.026 (0.015)	-0.023 (0.012)	-0.017 (0.077)
Age 50-59	0.010 (0.019)	-0.026 (0.018)	-0.011 (0.014)	-0.122 (0.100)
Age 60-64	0.007 (0.031)	-0.045 (0.029)	-0.027 (0.023)	-0.438 (0.431)
[No Schooling]				
Elementary School	0.109 (0.114)	0.138 (0.114)	0.151 (0.110)	0.034 (0.085)
Some High School	0.137 (0.113)	0.163 (0.113)	0.161 (0.110)	0.101 (0.082)
High School Graduate	0.140 (0.113)	0.157 (0.113)	0.169 (0.110)	0.030 (0.095)
Some Post-Secondary	0.134 (0.115)	0.157 (0.114)	0.169 (0.111)	0.005 (0.110)
University Graduate	0.244 (0.119)	0.288 (0.120)	0.243 (0.113)	0.362 (0.185)
Union	0.061 (0.013)	0.019 (0.013)	0.041 (0.011)	-0.094 (0.064)
Change Employers	--	-0.337 (0.030)	--	--
Industry Dummies	Yes	Yes	Yes	Yes
Sample Size	4,136	4,136	3,544	592

Notes: Robust standard errors are presented in parentheses. Excluded reference categories presented in square brackets. The union and industry dummies are based on accident employer information. The dependent variable in the regression is the change in log real hourly wages immediately before and after the worker's injury.

Table 3: Wage Regression Estimates of the Effect of Not Returning to the Pre-Injury Employer

	Pooled Sample		Age Subsamples		Educational Subsamples			Union Subsamples	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	No controls	With Controls	Young (20-39)	Old (40-64)	Less than High School	High School	More than High School	Nonunion	Union
Accident Employer	0.155 (0.016)	0.133 (0.015)	0.163 (0.020)	0.077 (0.023)	0.106 (0.019)	0.114 (0.032)	0.251 (0.042)	0.100 (0.023)	-0.008 (0.020)
Post-Injury	-0.254 (0.020)	-0.254 (0.020)	-0.260 (0.025)	-0.245 (0.031)	-0.246 (0.024)	-0.311 (0.042)	-0.216 (0.054)	-0.172 (0.028)	-0.409 (0.027)
Accident Employer*Post -Injury	0.241 (0.022)	0.241 (0.021)	0.245 (0.028)	0.233 (0.033)	0.227 (0.026)	0.301 (0.045)	0.226 (0.059)	0.150 (0.032)	0.400 (0.028)
[No Schooling]									
Elementary	--	0.174 (0.065)	0.290 (0.139)	0.184 (0.073)	--	--	--	0.097 (0.112)	0.195 (0.071)
Some High School	--	0.196 (0.065)	0.320 (0.138)	0.219 (0.073)	--	--	--	0.098 (0.113)	0.225 (0.071)
High School Graduate	--	0.227 (0.065)	0.363 (0.138)	0.247 (0.073)	--	--	--	0.143 (0.113)	0.248 (0.071)
Some Post-Secondary	--	0.240 (0.066)	0.364 (0.139)	0.262 (0.077)	--	--	--	0.108 (0.115)	0.287 (0.072)
University Graduate	--	0.224 (0.067)	0.355 (0.139)	0.243 (0.076)	--	--	--	0.166 (0.115)	0.259 (0.072)

Age	--	--	0.015 (0.001)	0.002 (0.001)	--	--	--	--	--
[Age 20-29]									
Age 30-39	--	0.092 (0.010)	--	--	0.050 (0.014)	0.130 (0.018)	0.158 (0.026)	0.128 (0.018)	0.030 (0.011)
Age 40-49	--	0.149 (0.011)	--	--	0.126 (0.013)	0.179 (0.021)	0.141 (0.032)	0.175 (0.020)	0.095 (0.011)
Age 50-59	--	0.166 (0.012)	--	--	0.135 (0.014)	0.167 (0.025)	0.277 (0.044)	0.144 (0.023)	0.127 (0.012)
Age 60+	--	0.078 (0.022)	--	--	0.048 (0.025)	0.069 (0.042)	0.233 (0.146)	0.118 (0.042)	0.025 (0.022)
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.087	0.138	0.198	0.067	0.118	0.166	0.219	0.103	0.121
Sample Size	4,136	4,136	1,896	2,240	2,655	967	514	1,511	2,604

Notes: Standard errors are presented in parentheses. The dependent variable for all of the regressions displayed in this table is the log of the respondent's real hourly wage. The excluded reference group is displayed in square brackets. Estimates for intercept are not presented. The data contain observations from immediately before and after the worker's injury, for a sample 4,171 males between the ages of 20 and 64.

Table 4: Matching Estimates with Bias Reduction of the Sample Average Treatment Effect for the Relative Loss in Log Real Hourly Wages for Workers who Remain with their Pre-Accident Employer

	(1)	(2)	(3)
Pooled Sample	0.303 (0.021)	0.305 (0.023)	0.289 (0.021)
Young Sample (age 20-39) [a]	0.311 (0.029)	0.322 (0.031)	0.312 (0.029)
Old Sample (age 40-64) [b]	0.309 (0.035)	0.308 (0.037)	0.304 (0.038)
Less than High School Graduate Sample [c]	0.273 (0.026)	0.275 (0.025)	0.276 (0.025)
High School Graduate Sample [c]	0.287 (0.043)	0.296 (0.044)	0.341 (0.045)
More than High School Graduate Sample [c]	0.432 (0.072)	0.414 (0.071)	0.402 (0.067)
Nonunion Sample	0.184 (0.025)	0.201 (0.026)	0.219 (0.026)
Union Sample	0.394 (0.036)	0.382 (0.038)	0.368 (0.038)

Notes: Standard errors are presented in parentheses. The wage loss variable is the change in real log wages for the worker immediately before and after his injury. Columns correspond to the following matching variables (except where noted otherwise): (1) matches based on pre-injury real wage and disability rating; (2) matches based on pre-injury real wage, disability rating, age dummies and educational attainment; and, (3) matches based on pre-injury real wage, disability rating, age dummies, educational attainment and location dummies.

[a] age dummies used in matching are for 20-29 and 30-39
[b] age dummies used in matching are for 40-49, 50-59 and 60-64.
[c] does not include the educational attainment dummies in the matching.

Table 5: Estimates from the Variance of Components Model

	Pooled Sample	Did Return to Pre-injury employer	Did Not Return to Pre-injury employer
α	0.638 (0.140)	0.602 (0.111)	0.945 (0.069)
σ_ω^2	0.068 (1.479)	0.055 (0.645)	0.006 (0.362)
σ_μ^2	0.108 (1.024)	0.062 (0.369)	0.193 (0.378)
Average σ_t^2	0.003	0.036	0.006
Newey Goodness of Fit Test Statistic	989.7 {<0.0001}	1,549 {<0.0001}	1,919 {<0.0001}
Number of Individuals	710	551	159

Notes: σ_t^2 is the average of the σ_t^2s for each year. Standard errors are present in parentheses. Curly braces contain p-values from chi-squared distribution for Newey's test statistic. The data consistent of a short panel on 710 males between the ages of 20 and 64.

Table A1: Moment Conditions for the Components-of-Variance Model

(1a)	$var(\log w_{it})$	=	$\sigma^2_{\omega} + \sigma^2_{\mu} + (1/(1-\alpha^2))\sigma^2_{t}$, for t = 2,…
(1b)	$var(\log w_{it})$	=	$\sigma^2_{\omega} + \sigma^2_{\mu} + \sigma^2_{t} + \alpha^2 \, \mathrm{var}(u_{i0})$, for t = 1
(2)	$cov(\log w_{it}, \log w_{it-1})$	=	$\sigma^2_{\omega} + (\alpha/(1-\alpha^2))\sigma^2_{t}$, for t = 2,…
(3)	$cov(\log w_{it}, \log w_{it-2})$	=	$\sigma^2_{\omega} + (\alpha^2/(1-\alpha^2))\sigma^2_{t}$, for t = 3,…
(4)	$cov(\log w_{it}, \log w_{it-3})$	=	$\sigma^2_{\omega} + (\alpha^3/(1-\alpha^2))\sigma^2_{t}$, for t = 4,…

Notes: In general, $cov(\log w_{it}, \log w_{it-S}) = \sigma^2_{\omega} + (\alpha^S/(1-\alpha^2))\sigma^2_{t}$. Row 1(b) provides the moment condition for $var(\log w_{it})$ in the initial time period, and the moment conditions for all subsequent periods are provided by row 1(a).

Figure 1: Wage Changes for Disabled Workers With Repeated Job Changes