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

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Abstract

Using data from the Survey of Ontario Workers with Permanent Impairments (1989–90), the authors examine the effects of work-related disabilities on the wage losses of disabled male workers. One important focus of the analysis is whether the size of disabled workers' wage losses was affected by whether they remained at or left the job where the accident occurred. The authors also estimate the longer-term persistence of wage shocks for disabled workers. The estimates suggest that wage losses were larger for disabled workers who did not return to work with their time-of-accident employer than for those who did return, with the latter earning 27% more. Furthermore, wages appear to have been more persistent for workers who did not return to their accident employer than for those who did return.

KEYWORDS: disabled workers, occupational injuries, wage losses from injuries

DISABLED WORKERS AND WAGE LOSSES: SOME EVIDENCE FROM WORKERS WITH OCCUPATIONAL INJURIES

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Using data from the Survey of Ontario Workers with Permanent Impairments (1989–90), the authors examine the effects of work-related disabilities on the wage losses of disabled male workers. One important focus of the analysis is whether the size of disabled workers' wage losses was affected by whether they remained at or left the job where the accident occurred. The authors also estimate the longer-term persistence of wage shocks for disabled workers. The estimates suggest that wage losses were larger for disabled workers who did not return to work with their time-of-accident employer than for those who did return, with the latter earning 27% more. Furthermore, wages appear to have been more persistent for workers who did not return to their accident employer than for those who did return.

A well-documented finding in the empirical literature on labor market earnings is that poor 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 use, the body mass index, the presence of mental illness, and overall self-reported health levels. In addition to these measures, a common approach for evaluating the impact of health on wages has been to examine the relationship between workers' earnings and their disability-related physical or mental limitations. This approach is popular because many researchers view a decrease in health

as a loss in overall earnings capacity due to a loss of general human capital, and examining the limitations caused by disabilities is a fairly straightforward way to test 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. These data contain administrative information on the nature of each injury as well as the worker's pre- and post-injury wages, enabling us to investigate the wage effects of several factors. Some features of this data set suit it particularly well to an investigation of the link between health and wages.

First, because of the unpredictability of the timing and nature of work accidents and the disabilities they occasion, the affected workers cannot have made anticipatory adjustments.

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Access to the data requires the permission of the Workplace Safety & Insurance Board of Ontario. For copies of the computer programs, please contact Michele Campolieti, Centre for Industrial Relations, University of Toronto, 121 St. George Street, Toronto, Ontario M5S 2E8; email: campolie@chass.utoronto.ca.

In other data sources containing information on disabilities suffered by workers, not all of the disabilities are unknown ahead of time.¹ For example, including degenerative diseases in an empirical analysis, as many studies have done, 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, our data are on workers identified as disabled not by self-report, but as judged by adjudicators from the Workers' Compensation Board of Ontario. In self-reporting, some individuals may describe themselves as disabled in order to justify weak labor market attachment, and this bias can limit the inferences that can be made about the effect of a disability on labor market outcomes (Bound 1991). Third, because our data include indications of injury type and severity, we can examine how the nature of the health problem affects labor market outcomes. Such an examination is not possible in studies that use more widely available labor market data sets. Fourth, the availability of pre- and post-injury wages in our data allows us to analyze the wage impact of disabling injuries in a dynamic context.

We focus on two issues. First, we compare the short-term wage losses of disabled workers who returned to work with their time-of-accident employer (hereafter referred to, for brevity, as the "accident employer") with the wage losses of those who did not. We determine the degree to which the immediate drop in a worker's wages after a disabling injury is due to the destruction of general human capital and the degree to which it is affected by remaining at the accident 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.

¹Although the effects of the accidents are unknown ahead of time, workers can assess the risks of injury associated with a job.

Literature Review and Theory

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, is similar to the rationale for investing in health capital. Grossman (1972) formalized this idea with a model in which health directly affects 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 presented analyses of the effects of disabilities on earnings using longitudinal data. Boden and Galizzi (2003) studied 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 exhibited similar earnings losses in the quarter after they were injured, women tended to fare worse than men in the years following the injury. Whereas male earnings exhibited a modest recovery during this period, female earnings recovered more slowly, which the authors took as being consistent with discriminatory behavior against women.

Charles (2003) considered the effect of disabilities on worker behavior over time using a human capital framework, which incorporated health capital, and observed that if a disability diminishes the health capital 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 health capital and, consequently, the greater the wage loss. Second, older workers should exhibit greater wage losses than younger workers immediately after the onset of a disability, because they have more health capital to be eliminated by a disability. Third, younger workers should exhibit larger growth in post-disability

earnings than do older workers, because they have a greater incentive to invest in disability capital to assist them in their new state of health. Since Charles (2003) used the PSID, his sample of workers reported whether they were disabled, but not the severity or type of disability from which they suffered. As a result, Charles measured the "chronicity" of the disability, which was equal to the number of times the worker reported being disabled during his study period. With this measure he found that greater chronicity was associated with larger wage losses. He also found that younger workers with disabilities exhibited smaller wage losses and more robust wage gains than did older workers. All these findings are consistent with the human capital model he proposed.

A limitation of the papers in the existing literature examining the impact of disabilities on earnings is that virtually all of them have relied on self-reports to identify disabled workers. We cannot know how many (if any) workers who are included in such a study identified themselves as "disabled" to justify weak labor market attachment (Bound 1991). Another limitation is that some of the health problems that could result in a disability have a long onset, so individuals could 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. In contrast, the administrative data that are employed in this paper can circumvent such problems because the disability assessments they contain are based on medical reports regarding the nature and severity of the disability. In addition, because all the observations in our data set are for workers who suffered work-related accidents, none of the disabilities represented in our sample were ones for which workers could have made adjustments ahead of time.

From a theoretical perspective, disabled workers can be seen to maximize a static or intertemporal utility function in which they decide to allocate their time to the labor market or leisure. Disability benefits can influence these decisions. Consequently, most disability benefits will have both income and substitution effects in these models. Burkhauser, Butler, and Weathers (2002)

also presented another view of the disabled person's choice problem. They posited that the disabled worker will consider the loss of labor market earnings as the opportunity cost of leaving the labor market to collect benefits. In this framework, the point of reference for workers who are deciding whether to withdraw from the work force is the point at which the opportunity cost of leaving the labor market equals the marginal benefits of collecting disability benefits.

The sample analyzed in this paper is comprised of workers with occupational injuries that resulted in permanent impairments. The next section will provide more details on these workers and the benefits they received. However, the benefits these workers received would affect the theoretical frameworks described above. First, the workers studied in this paper received permanent disability benefits that were paid irrespective of labor market earnings, with no reductions to offset earnings. This means that there were no claw-backs to benefits if the workers earned above a certain threshold, unlike in other disability programs. Consequently, these benefits did not have a substitution effect, only an income effect (Hyatt 1996; Campolieti, Gunderson, and Krashinsky 2006). Second, because a disabled worker in this sample could collect permanent disability benefits with no reductions for his or her labor market earnings, that person did not have to balance the opportunity cost of leaving the labor market with the marginal benefits associated with benefit receipt. The decisions to make on the margin for the disabled workers in this sample therefore differed from those for individuals collecting the DI benefits provided by the Social Security Administration or the Canada/Quebec Pension Plan disability program.

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 administered by the Ontario Workers' Compensation Board (WCB) between June 12, 1989 and August 31, 1990. In Ontario, workers who never fully recover from their workplace injury and suffer some loss in their capacity to earn are called permanently disabled. The workers in our sample 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 a disability rating, which would be used to compute the permanent disability benefits.² The permanent disability benefits are computed as the disability rating multiplied by the pre-injury earnings subject to a statutory earnings ceiling. These benefits are paid as a lump sum and are not conditional on any wage losses or labor market conditions. The disability rating is determined during the physical exam, and it maps the worker's disabilities into a percentage of lost earnings capacity. For example, in Ontario the loss of an arm has a disability rating of 30%.

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 accident employer or a new employer and the wages earned at the post-injury jobs. These are retrospective reports of the worker's employment history, which contain information on a number of jobs after the injury as well as the 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 accident employer. The survey data also include 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 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% means that the worker had lost 25% of 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, and 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 (standardized codes assigned to injuries and health problems). To estimate a regression on 34,032 claims filed between 1984 and 1989, Hyatt used selected Ontario WCB administrative records that included actual worker disability ratings. We applied the coefficient estimates from Hyatt's regression equation to our data to create a value of the expected disability rating for each person in our sample from the SOWPI based on his demographic characteristics and injury information.

While the disability rating can be used to measure the extent of the loss of functional capacity, it may not capture the actual earnings losses. For example, Weiler (1980) considered the effects of a 30% disability rating (the loss of an arm) on a lawyer and a laborer. The earnings capacity of a lawyer who loses an arm in the course of employment (driving to court) would not be affected to a large extent. In contrast, the consequences of a lost arm for the earnings of a laborer would be much more severe.³ The disability

²Internal assessments of the SOWPI by WCB personnel indicated that the data were representative of the population of permanent disability claimants in Ontario.

³Disability rating schedules contain lists of injuries and percentages of lost earnings capacity that correspond to different injuries. However, the injury schedules often exclude injuries to the trunk, internal organs, nervous system, and other body systems (Berkowitz and Burton 1987).

ratings for some injuries, such as amputation injuries, are also clearly defined. However, Hyatt (1996) noted that there is room for discretion on the part of the examining physician for some sorts of injuries, particularly soft tissue and musculoskeletal injuries, so there can be some uncertainty or variation in the disability ratings assigned to these injuries according to the examining physician.

We use the information in the survey to create two data sets. First, we use the information on a worker's pre-injury job and first post-injury job to examine the short-term loss in wages. We can only estimate this regression for workers who returned to work. We include male workers aged 20 to 64 who had accidents between 1979 to 1989, which results in a sample of 4,115 men 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 use this second data set to obtain estimates of the persistence in the wages of workers after their injury, in order to examine the longer-term wage consequences of a disability. 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. After imposition of our sample restrictions—only men between the ages of 20 and 64 who had accidents between 1979 and 1984—the sample in this data set consisted of 710 men. 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. Within both data sets we consider two subsamples: workers who initially returned to work with their accident employer and then left for other jobs, and workers who never returned to work with their accident employer after they re-entered the labor market. This comparison is new to the literature and could be 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 who 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 returned to their

accident employer and lost about 5% of their wages after an injury. The age distribution is almost evenly split between older (40–64) and younger (20–39) men, but the majority of these men had 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 had lost 11% of his earnings capacity. The proportion of union workers in the sample (63%) was higher than the union density ratio across Canada (30–35% during our study period), because our sample over-represents blue-collar occupations, which tend to have higher concentrations of union workers.

We also split the sample into two groups: workers who returned to their accident employer and those who did not. The group that returned to their accident employer had higher pre-injury wages than the group that left. A number of factors could contribute to the difference between the two groups in pre-injury wages. Some of the difference could be attributable to differences in firm-specific human capital, which could reflect higher recruiting, hiring, and training costs, and hence higher turnover costs. On the other hand, the two groups also differed in unionization rates, so the difference could also be partly due to a union wage premium. Interestingly, both groups had similar expected disability ratings, but the wage losses after their injuries were very different. Workers who returned to their accident employer had minor wage losses of just over 1% on average, but workers who did not return to their accident employers had wage losses of approximately 26%. This striking difference in wage losses does not appear to have arisen from major differences in other observable variables, such as age or education. This pattern of findings suggests that returning to one's accident employer is a quite important determinant of wages for disabled workers. In particular, the worker might have firm-specific human capital, which might not be valued by other employers, or strong union protection at the accident employer.

Table 1. Descriptive Statistics.

<i>Independent Variable</i>	<i>Pooled Sample</i>	<i>Did Return to Accident Employer</i>	<i>Did Not Return to Accident Employer</i>
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)
Union	0.632 (0.482)	0.678 (0.467)	0.358 (0.480)
Number of Individuals	4,115	3,530	585

Note: The sample consists of male workers aged 20 to 64 from the SOWPI.

Empirical Models

Regression Analyses

A simple approach for considering the relative impact of not returning to the accident employer involves examining the wages of the disabled workers using the regression

$$(1) \quad \log w_{it} = \beta_0 + \beta_1 \text{AccEmp}_{it} + \beta_2 \text{PostInjury}_{it} + \beta_3 \text{PostInjury}_{it} * \text{AccEmp}_{it} + X_{it}'\gamma + u_{it}$$

where w_{it} is the real hourly wage, AccEmp_{it} is a dummy variable equal to 1 if the worker is employed by the accident employer, PostInjury_{it} is a dummy variable that takes the value 1 for the post-injury observation, $\text{PostInjury}_{it} * \text{AccEmp}_{it}$ 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 pre-

mium” for disabled workers who returned to work with their accident employers, relative to those who left, after their injury. However, this is a naive estimator, because it ignores any potential biases due to selection effects for workers who did and did not return to their accident employer. To address these selection effects (based on observables), we use matching estimators to compare similar individuals (based on observable characteristics) in these two groups of workers.

Matching Analyses

We also obtain estimates of the effect of remaining with the accident employer using a matching estimator. We provide a brief description of the estimator here; the details can be found in Abadie and Imbens (2002).

Let the observed outcome (the change in log wages), Y_i , be such that

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

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, that is, 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) showed that a simple matching estimator will be biased in finite samples if the matching is not exact. Consequently, they proposed 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 $\tilde{Y}_i(0)$ and $\tilde{Y}_i(1)$. The sample average treatment effect can then be computed as

$$(3) \quad \hat{\tau}_M = \frac{1}{N} \sum_{i=1}^N (\tilde{Y}_i(1) - \tilde{Y}_i(0)).$$

The estimates from the bias-corrected matching approach can be compared with the regression estimates to determine the potential impact on the estimates of a selection bias due to observables. The matching estimator cannot account for selection based on unobservables. However, through the use of a rich array of information on observed characteristics, it is possible that the matching procedures may control for the effect of unobservable characteristics to some extent if they are correlated with the observed characteristics of individuals.

Components-of-Variance Model

The regression and matching approaches discussed above are appropriate for analyzing short-term wage losses for disabled workers, but we are also interested in the long-term effects 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

$$(4) \quad \log w_{it} = \omega_i + v_t + u_{it} + \mu_{it},$$

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

The model presented in equation (4) represents wages as a person-specific constant, ω_i , an aggregate effect, v_t , and 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 second 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 u_{it} 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 A1.⁴ The parameters of interest from this model are estimated by minimizing the quadratic form

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

where m is a vector of sample moments, $f(\Xi)$ is a vector of 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 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 to 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 (for example, Baker 1997; Baker and Solon 2003). We also compute a goodness of fit test statistic suggested by Newey (1985) for each of the models we estimated.

Empirical Results

Before presenting our estimates of the wage effects of remaining at the accident employer, 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 in the log of real wages (that is, post-injury minus pre-injury) for workers on controls for age, educational attainment, pre-injury union status, the expected disability rating, dummies for the part of the body injured

and the nature of the injury, and industry dummies. The estimates, presented in Table 2, do not show a statistically significant relationship between most of the age dummies and the change in wages. Likewise, most of the education dummies—with the exception of the dummy for a university degree—were not statistically significant determinants of the loss in earnings. However, union status did have a statistically significant effect on the wage losses. Another important point that echoes Table 1 arises in column (2) of Table 2: an indicator variable for whether or not the worker returned to his accident employer is highly statistically significant. The disability rating is not a statistically significant determinant of the loss in earnings. Similarly, most of the injury dummies do not have statistically significant coefficients.

We also estimated the regressions splitting the sample into the groups that did and did not return to their accident employer. The estimates in column (3) of Table 2 indicate that most of the age and educational attainment dummies are not statistically significant determinants of the change in wages for this group. Only the industry dummies, which are not presented in Table 2, and the union status of the accident employer are statistically significant determinants. These findings can be interpreted as suggesting that firm-specific factors were determining how these workers fared after their injuries. The positive, statistically significant impact of pre-injury union status suggests that a worker who may benefit from institutional protection after his injury can still receive generally equivalent wages after his injury.

For workers who did not return to their accident employer, the regression results are somewhat similar (column 4, Table 2). The estimates indicate that neither age nor education—with the exception of a university degree—had a statistically significant impact on the change in wages. The pre-injury industry dummies are statistically significant determinants of a worker's wage change, but the control for union status is not.

The results in Table 2 demonstrate that “typical” human capital variables, such as age and education, were (for the most part) not statistically significant determinants of the

⁴To 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 we were able to construct a two-year covariance for the worker. The vast majority of workers in the sample of job changers had yearly job changes, so it was possible to obtain good estimates of the first-, second-, and third-order covariances for wages.

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

<i>Independent Variable</i>	<i>Pooled Sample</i>		<i>Did Return to</i>	<i>Did Not Return to</i>
	<i>(1)</i>	<i>(2)</i>	<i>Accident Employer</i>	<i>Accident Employer</i>
			<i>(3)</i>	<i>(4)</i>
Change Employers	—	-0.341 (0.031)	—	—
<i>Age [20–29]</i>				
Age 30–39	-0.028 (0.017)	-0.038 (0.016)	-0.027 (0.012)	-0.060 (0.072)
Age 40–49	-0.002 (0.017)	-0.030 (0.016)	-0.026 (0.012)	-0.019 (0.081)
Age 50–59	0.004 (0.019)	-0.029 (0.018)	-0.013 (0.014)	-0.111 (0.104)
Age 60–64	-0.004 (0.032)	-0.053 (0.030)	-0.030 (0.023)	-0.436 (0.419)
<i>Education [No Schooling]</i>				
Elementary School	0.105 (0.112)	0.134 (0.112)	0.151 (0.110)	0.017 (0.112)
Some High School	0.138 (0.112)	0.164 (0.112)	0.162 (0.110)	0.121 (0.083)
High School Graduate	0.139 (0.112)	0.156 (0.112)	0.171 (0.110)	0.046 (0.098)
Some Post-Secondary	0.129 (0.113)	0.153 (0.113)	0.167 (0.110)	-0.017 (0.112)
University Graduate	0.250 (0.118)	0.294 (0.119)	0.253 (0.113)	0.300 (0.189)
Union	0.063 (0.014)	0.021 (0.013)	0.041 (0.011)	-0.103 (0.066)
Expected Disability Rating	0.023 (0.162)	0.034 (0.153)	-0.066 (0.117)	0.920 (1.015)
<i>Part of Body Injured [Injuries to the Head]</i>				
Injuries to the Hands and Arms	-0.026 (0.037)	-0.019 (0.034)	-0.034 (0.029)	0.104 (0.153)
Injuries to the Trunk	0.040 (0.019)	0.037 (0.017)	0.020 (0.014)	0.189 (0.107)
Injuries to the Back	-0.037 (0.027)	-0.023 (0.025)	-0.022 (0.023)	0.047 (0.108)
Injuries to the Lower Extremities	-0.004 (0.024)	0.008 (0.022)	-0.013 (0.018)	0.106 (0.116)
Injuries to Multiple Body Parts	-0.023 (0.028)	-0.017 (0.026)	-0.014 (0.021)	0.042 (0.136)
<i>Nature of Injury [Unspecified]</i>				
Other	0.043 (0.029)	0.050 (0.030)	0.022 (0.016)	0.197 (0.169)
Dislocation/Fracture	-0.002 (0.024)	0.002 (0.025)	-0.051 (0.021)	0.222 (0.104)
F-Test Statistics for Age	5.25 {0.022}	3.09 {0.046}	3.25 {0.039}	2.65 {0.033}
F-Test Statistics for Education	2.47 {0.043}	3.19 {0.013}	3.15 {0.014}	2.78 {0.026}
Sample Size	4,115	4,115	3,530	585

Notes: Robust standard errors in parentheses; excluded reference categories in square brackets. The union and industry dummies are based on accident employer information. All regressions include six indicator variables for major industry groupings. The dependent variable in the regression is the change in log real hourly wages (before and after the worker's injury).

Table 3. Wage Regression Estimates of the Effect of Returning to the Accident Employer.

Independent Variable	Pooled Sample		Age Subsamples		Educational Subsamples			Union Subsamples	
	(1) No Controls	(2) With Controls	(3) Young (20-39)	(4) Old (40-64)	(5) Less Than High School	(6) High School	(7) More Than High School	(8) Nonunion	(9) Union
Accident Employer	0.154 (0.016)	0.133 (0.015)	0.158 (0.020)	0.077 (0.023)	0.106 (0.019)	0.111 (0.032)	0.251 (0.042)	0.100 (0.023)	-0.008 (0.020)
Post-Injury	-0.256 (0.020)	-0.256 (0.020)	-0.265 (0.026)	-0.245 (0.031)	-0.248 (0.025)	-0.315 (0.042)	-0.216 (0.054)	-0.172 (0.028)	-0.409 (0.027)
Accident Employer * Post-Injury	0.243 (0.022)	0.243 (0.021)	0.250 (0.028)	0.233 (0.033)	0.230 (0.027)	0.305 (0.045)	0.226 (0.059)	0.150 (0.032)	0.400 (0.028)
<i>Education [No Schooling]</i>									
Elementary	—	0.173 (0.065)	0.290 (0.139)	0.184 (0.073)	—	—	—	0.097 (0.113)	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)	0.361 (0.139)	0.247 (0.073)	—	—	—	0.143 (0.113)	0.248 (0.071)
Some Post-Secondary	—	0.242 (0.066)	0.352 (0.139)	0.262 (0.077)	—	—	—	0.108 (0.115)	0.287 (0.072)
University Graduate	—	0.222 (0.066)	0.352 (0.139)	0.243 (0.076)	—	—	—	0.166 (0.115)	0.259 (0.072)
Age	—	—	-0.015 (0.001)	0.002 (0.001)	—	—	—	—	—
<i>Age [20-29]</i>									
Age 30-39	—	0.091 (0.010)	—	—	0.050 (0.014)	0.128 (0.018)	0.158 (0.026)	0.128 (0.018)	0.030 (0.011)
Age 40-49	—	0.149 (0.011)	—	—	0.124 (0.013)	0.179 (0.021)	0.152 (0.032)	0.175 (0.020)	0.095 (0.011)
Age 50-59	—	0.169 (0.011)	—	—	0.137 (0.014)	0.167 (0.025)	0.279 (0.044)	0.144 (0.023)	0.127 (0.012)
Age 60+	—	0.078 (0.022)	—	—	0.048 (0.025)	0.069 (0.042)	0.241 (0.145)	0.118 (0.042)	0.025 (0.022)
Location Dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.088	0.139	0.198	0.067	0.191	0.164	0.222	0.103	0.121
F-Test Statistics for Age	—	-67.96 {<0.001}	—	—	33.91 {<0.001}	25.40 {<0.001}	15.97 {<0.001}	24.62 {<0.001}	34.94 {<0.001}
F-Test Statistics for Education	—	7.94 {<0.001}	4.92 {<0.001}	5.15 {<0.001}	—	—	—	2.42 {<0.001}	9.61 {<0.001}
Sample Size	4,115	4,115	1,884	2,231	2,643	962	510	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 before and after the worker's injury for males between the ages of 20 and 64. The dependent variable in these regressions is the log of the worker's wage.

change in wages, but the loss of important institutional advantages could be important for these workers. For instance, a worker who lost his union status was losing the benefit of his seniority at the firm, and it also appears that some workers lost firm-specific insurance if they left their accident employer. A standard (labor supply) model would imply that a worker is paid his marginal productivity, so a new post-injury employer is simply paying the worker his marginal product. However, men who could return to their accident employers and maintain their firm-specific capital (even in the face of large decreases in general human capital) did not have statistically significant wage decreases. This result runs contrary to the view that the destruction of human capital due to disability must reduce wages for workers in all cases. It is consistent, however, with the interpretation that the worker is insured by the firm through a long-term contract (Abowd and Card 1987).⁵

Regression 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 Table 3. In the first column, our regression only includes 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). 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 and the injury

dummies are not included as explanatory variables in these regressions because they are only available for the post-injury data. 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 22.6% decline in wages ($\exp(-0.256) - 1$), which indicates that post-injury wages will be smaller. More important, the interaction term between POSTINJURY and the accident employer dummy variable indicates that post-injury wages were higher for workers who remained at the accident employer after their injury, relative to those who left. This estimate is also quite large, suggesting a difference of about 27.5% ($\exp(0.243) - 1$).

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 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 aged 20–39 (“young” workers) and workers aged 40–64 (“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%, $\exp(0.233) - 1$) is about the same as the estimate for younger workers (about 28%, $\exp(0.250) - 1$). More surprisingly, the estimate for older workers is not statistically 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 none of the three columns is there a 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.

⁵Abowd and Card (1987) distinguished 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).

These results tend to run counter to the hypothesis that wage losses should be greater for workers with larger amounts of general human capital. But they do suggest that firm-specific human capital may be an important factor in this analysis, and in a very particular way. Although there was a large penalty to leaving the firm after suffering a disabling injury, it did not differ between older and younger workers. The implication is that if the penalty was due to losing firm-specific human capital, this capital was amassed quickly by workers and did not increase during their tenure at the firm.

We also estimate the regression for workers who were members of unions compared with those who were not (columns 8–9 of Table 3). The estimates in column (8) suggest that non-unionized workers who remained with their accident employers earned 16% ($\exp(0.15) - 1$) more than non-union workers who left their non-union employer after their injury, but this estimate is 49% ($\exp(0.40) - 1$) 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). It is also supportive of the hypothesis that disabled workers exhibited large wage losses after their injuries not because of the destruction of general human capital by the injury, but rather because of the loss of firm-specific benefits, such as seniority at the firm. These institutional benefits were lost because the disabled workers moved to a new employer when they re-entered the labor market. The magnitude of the difference in estimates between unionized and non-unionized workers is remarkably large—much larger, for example, than the average wage loss for the entire sample, which was calculated as 5% in Table 1.

In order to provide a benchmark for our estimates, we also used data from the Canadian Labour Market Activity Survey (LMAS), which covers the years 1988–90, to estimate the wage effect of remaining at an employer for able-bodied workers relative to involuntarily displaced workers. It should be borne in mind that the wage dynamics for the able-bodied workers may differ from those for the disabled workers in our sample,

so the estimates may not be strictly comparable.⁶ The estimates in Table A2 indicate that able-bodied workers who remained with their employers earned about 19.1% ($\exp(0.175) - 1$) more than workers who were involuntarily displaced. The estimates in Table A2 are about 8 percentage points smaller than the estimates for the pooled sample in Table 3.

Matching Analysis 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. (2004), from bias-reduced matching estimators for the difference in real log wages for workers remaining and leaving the accident employer. The advantage of the matching estimator over a regression analysis is that it matches individuals from two groups that are similar on the basis of predetermined observable characteristics. The matching approach is particularly useful for our study because we can consider many dimensions to match similar workers who did and did not leave their pre-injury firms after their disabling accidents.

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, the part of the body that was injured, the nature of the injury, and expected disability ratings. These are important variables for the matching procedure because using the pre-injury wage will pair individuals with similar levels of pre-disability productivity, matching on the type of injury will ensure that workers with similar injuries are compared, and the expected disability rating will allow us to compare workers who suffer injuries of similar severity. The results shown in the second and third columns of Table 4 are from analyses that allow for a further refinement of the matching process by using more variables to match the workers. The second column

⁶For example, 36% of the disabled workers who did not change employers experienced a fall in wages in our data.

Table 4. Matching Estimates with Bias Reduction of the Sample Average Treatment Effect for Remaining with the Accident Employer after Injury on Change in Wages.

Sample	(1)	(2)	(3)
Pooled Sample	0.319 (0.021)	0.293 (0.023)	0.286 (0.020)
Young Sample (age 20–39) ^a	0.305 (0.029)	0.332 (0.031)	0.286 (0.036)
Old Sample (age 40–64) ^b	0.288 (0.035)	0.288 (0.035)	0.286 (0.036)
Less Than High School Graduate Sample ^c	0.284 (0.026)	0.268 (0.025)	0.247 (0.024)
High School Graduate Sample ^c	0.302 (0.047)	0.315 (0.045)	0.351 (0.045)
More than High School Graduate Sample ^c	0.417 (0.070)	0.452 (0.071)	0.452 (0.082)
Nonunion Sample	0.200 (0.026)	0.180 (0.025)	0.205 (0.026)
Union Sample	0.395 (0.038)	0.404 (0.037)	0.379 (0.038)

Notes: Standard errors are presented in parentheses. The outcome variable is the change in real log wages for the worker immediately before and after his injury, and the treatment variable is whether the worker returned to the time-of-accident employer. Columns correspond to the following matching variables (except where noted otherwise): (1) matches based on pre-injury real wage, expected disability rating, the body part that was injured, and the nature of the injury; (2) matches based on pre-injury real wage, expected disability rating, the body part that was injured, the nature of the injury, age dummies, and educational attainment; and (3) matches based on pre-injury real wage, expected disability rating, the body part that was injured, the nature of the injury, age dummies, educational attainment, and location dummies.

^aAge dummies used in matching are for 20–29 and 30–39.

^bAge dummies used in matching are for 40–49, 50–59, and 60–64.

^cDoes not include the educational attainment dummies in the matching.

matches based on the pre-injury wage, the part of the body that was injured, the nature of the injury, the expected disability rating, age, and educational attainment, while the results in the third column reflect the inclusion of all the variables in the second column as well as dummy variables for geographic location. The location dummies could be important because of differences between 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 the 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 indicate that the SATEs on the difference in log wages are between 0.29 and 0.32 for the

pooled sample. All of these estimates are statistically different from zero at conventional significance levels and are not overly sensitive to the variables used to create the matches. The second and third rows demonstrate that the estimates of the wage premium for workers who remained with their firm are about the same, regardless of whether they were young or old, which corresponds with the regression results in Table 3. A more interesting result is found in rows 4–6, which indicate that the impact of remaining with the firm increased with the educational attainment of the worker. This result differs from those in Table 3, which did not exhibit such a pattern. This suggests that there may be selection issues for more educated workers that are affecting the regression estimates in Table 3. It also suggests that the advantage of remaining at the pre-injury firm stemmed from maintaining firm-specific

Table 5. Estimates of the Components-of-Variance Model.

<i>Description</i>	<i>Pooled Sample</i>	<i>Did Return to Accident Employer</i>	<i>Did Not Return to Accident Employer</i>
α	0.638 (0.140)	0.602 (0.111)	0.945 (0.069)
σ_w^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_i^2	0.003	0.036	0.006
Newey's 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_i^2 is the average of the σ_i^2 s for each year. Standard errors in parentheses; p-values from chi-squared distribution for Newey's test statistic in curly brackets. The data consist of a short panel on 710 men between the ages of 20 and 64.

capital, and this benefit does appear to have increased with education. The last two rows of Table 4 confirm what was established in the regression results: remaining with the accident employer was enormously more beneficial for union workers than for non-union workers. This suggests that the loss of firm-specific factors (like union seniority) is very important in determining the wage losses of disabled workers.

Components-of-Variance Estimates

We investigate the longer-term effects of a disability on wages with the components-of-variance model (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 accident employer but then left the employer for another job; and the subsample that includes workers who did not return to work with their accident 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.

For the pooled sample, our estimate of α , which captures the degree of persistence in the data, is about 0.64 and statistically significantly different from zero. When we restrict the sample to workers who initially returned to work with the accident employer,

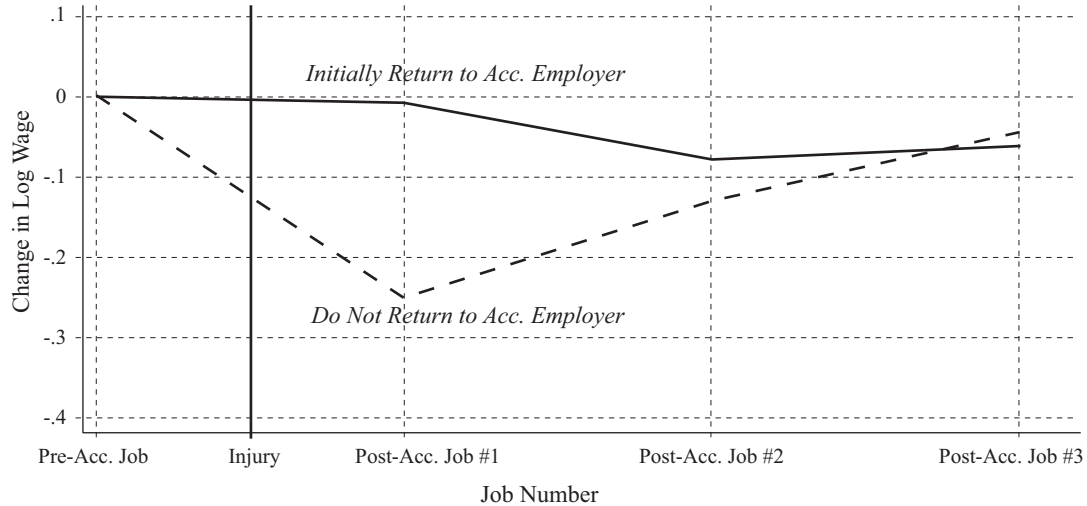
the estimate of α is slightly smaller, 0.60. On the other hand, when we estimate the model on the sample of workers who never returned to work with the accident employer, the estimate of α is much larger, about 0.95. This suggests that there was much greater persistence in the wages of the workers who never returned to work with their time-of-accident employers. This pattern is illustrated in Figure 1. There was a substantial change in wages for workers who left their employer right after their injury, but not for those who remained. However, the cumulative change in wages between the two groups became more similar as time passed.

To examine the implication of persistence in wages, we considered the effect of a one-unit change 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, a change in wages is a change in the first-order autoregressive component. This means that the effect of 1-unit change in current wages on the discounted average of future wages is $\frac{1-\beta}{1-\alpha\beta}$. If we assume that $\beta = 0.926$ (that is, a discount rate of 8%), this will equal 0.167 for the workers who returned to the accident employer and then switched employers. However, for workers who never returned

Figure 1. Wage Changes for Disabled Workers with Repeated Job Changes.



to their accident employer, it takes a value of 0.592. The first estimate implies that a 10% decrease in current wages decreases the discounted average of future wages by 1.7%. The second estimate implies a much larger effect. In particular, a 10% decrease in current wages decreases the discounted average of future wages by 5.9%.

Alternative Explanations and Estimates

The discussion in this section has highlighted the loss of firm-specific factors, such as firm-specific human capital, seniority, and other institutional factors, as an explanation for disabled workers' wage losses. However, a few other explanations could also be consistent with the wage losses we observe. First, workers who do not return to their accident employer may also be less likely to return to their accident occupation, thus losing any risk premiums they earned in that occupation. Second, if work absence is more prolonged for workers who do not return to their accident employer than for those who do, the former may suffer a larger loss of human capital. Third, the accident employer, due to various institutional pressures, may ensure that returning injured employees suffer no wage loss (a "guilt premium").

Our data do not allow us to address the first or third alternative explanations, but they do contain information on the duration of work absences.

We find that the data are indeed consistent with the second hypothesis described above: the mean duration of an absence from work for a worker who returned to work with an accident employer was 31.5 weeks, versus 75.9 weeks for a worker who returned to work with a different employer. To examine the robustness of our estimates with respect to this additional factor, we included the duration of the work absence in the list of variables used to find matches. The new estimates of the effect of remaining at the accident employer on the change in wages after an injury based on the matching procedure are presented in Appendix Table A3.

Including the duration of the work absence as a variable to obtain matches between workers who returned to the accident employer and those who did not typically reduces the estimates of the effect of remaining with the accident employer by about 0.08 to 0.10. For example, in Table A3 the estimates for the pooled sample in the first row lie between 0.204 and 0.215, compared to the estimates of about 0.286 to 0.319 in the first row of Table 4, which do not match based on the duration

of the work absence. While matching on the duration of the work absence reduces our estimates, they are still relatively large (in most cases, 0.20 or larger). In addition, we still observe the same patterns as in the estimates that were presented earlier.

Because we do not have information on changes in industry or occupation for the post-injury jobs, we could not investigate the effects of these shifts on the wage and earnings losses of disabled persons. This issue—which has been unaddressed, as well, in previous empirical work (for example, Charles 2003; Boden and Galizzi 2003)—could be examined using more conventional panel data sets. A test of the third, “guilt premium” alternative explanation we described in this section would also be of interest for future research.

Concluding Remarks

We have investigated how work-related accidents that resulted in permanent impairments of a sample of male workers in Ontario affected these disabled workers’ subsequent wages. We examined both the short- and long-term effects of a disability on hourly wages. Our main finding is that post-injury wage dynamics were markedly affected by whether or not the disabled worker returned to work with his time-of-accident employer.

Examining short-term wage losses with a regression-based approach, we found that typical human capital regressors generally do not have a statistically significant impact on the change in wages exhibited by workers who were disabled, but other variables are extremely important in this framework. Specifically, union coverage in the job at which the injury occurred, and whether or not the worker remained at his accident employer,

were highly statistically significant determinants of wage losses. In fact, a worker’s short-term wage path crucially depended on whether or not he remained at his accident employer. Our estimates indicate that workers who remained at their accident employer firm earned 27% more than workers who left. We also estimated these regressions on different subsamples and found that this difference was 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 wages occurs through the loss of firm-specific benefits, such as a long-term contract, that protect workers against negative health shocks or losses of firm-specific human capital. When we used a matching estimator to examine the loss in wages, we found that the results were generally similar to our regression estimates, but that the benefits of remaining at the accident employer were greater for more educated workers.

We examined the longer-term consequences of a disability on wages with a components-of-variance model, based on panel data we constructed with information on workers who had multiple changes in jobs. These estimates also indicate that the effect of a disability on wages depended on whether the worker returned to his accident employer. An earnings shock was particularly persistent in the wages of disabled men who never returned to work with their accident employer after they recovered from their injury.

Overall, the evidence we present documents an important aspect of earnings dynamics for disabled men that has not been discussed before in the literature. Specifically, disabled men suffer much smaller wage losses if they are able to maintain their employment with the firm at which the injury occurred.

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

(1a)	$var(\log w_{it}) = \sigma_w^2 + \sigma_i^2 + (1/(1-\alpha^2))\sigma_t^2$, for $t = 2, \dots$
(1b)	$var(\log w_{it}) = \sigma_w^2 + \sigma_i^2 + \sigma_t^2 + \alpha^2 var(u_{i0})$, for $t = 1$
(2)	$cov(\log w_{it}, \log w_{i,t-1}) = \sigma_w^2 + (\alpha/(1-\alpha^2))\sigma_t^2$, for $t = 2, \dots$
(3)	$cov(\log w_{it}, \log w_{i,t-2}) = \sigma_w^2 + (\alpha^2/(1-\alpha^2))\sigma_t^2$, for $t = 3, \dots$
(4)	$cov(\log w_{it}, \log w_{i,t-3}) = \sigma_w^2 + (\alpha^3/(1-\alpha^2))\sigma_t^2$, for $t = 4, \dots$

Notes: In general, $cov(\log w_{it}, \log w_{i,t-s}) = \sigma_w^2 + (\alpha^s/(1-\alpha^2))\sigma_t^2$. 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).

Table A2
Estimates of the Effect of Remaining at Employer on Wages Based on Data from the Labour Market Activity Survey (1988–1990) for Non-Disabled Workers

<i>Description</i>	<i>(1)</i>	<i>(2)</i>	<i>(3)</i>
Dummy for Non-Displaced Workers	0.175 (0.005)	0.175 (0.005)	0.173 (0.005)
Demographic and Industry Controls	No	Yes	Yes
Union Dummy	No	No	Yes
Sample Size	17,128	17,128	17,128

Notes: Standard errors in parentheses. The dependent variable is wages and the dummy for non-displaced workers takes the value 1 if the worker was not displaced from his job and the value 0 if the worker was involuntarily displaced from the job (fired, laid off, or plant/business closing). The data used in the regression included male workers aged 20 to 64 and consist of panel data from 1988 to 1990. The demographic controls include age, educational attainment, and marital status.

Table A3
Matching Estimates with Bias Reduction of the Sample Average Treatment Effect for Remaining with the Accident Employer after Injury on Change in Wages, with Matching on Duration of Work Absence

<i>Sample</i>	<i>(1)</i>	<i>(2)</i>	<i>(3)</i>
Pooled Sample	0.206 (0.025)	0.215 (0.023)	0.204 (0.021)
Young Sample (age 20–39) ^a	0.218 (0.034)	0.248 (0.033)	0.261 (0.031)
Old Sample (age 40–64) ^b	0.218 (0.040)	0.215 (0.039)	0.227 (0.040)
Less Than High School Graduate Sample ^c	0.189 (0.028)	0.182 (0.027)	0.186 (0.025)
High School Graduate Sample ^c	0.293 (0.051)	0.285 (0.051)	0.261 (0.050)
More Than High School Graduate Sample ^c	0.287 (0.077)	0.327 (0.076)	0.371 (0.088)
Nonunion Sample	0.086 (0.029)	0.108 (0.028)	0.119 (0.027)
Union Sample	0.333 (0.046)	0.304 (0.041)	0.302 (0.042)

Notes: Standard errors are presented in parentheses. The outcome variable is the change in real log wages for the worker immediately before and after his injury, and the treatment variable is whether the worker returned to the time-of-accident employer. Columns correspond to the following matching variables (except where noted otherwise): (1) matches based on pre-injury real wage, expected disability rating, the body part that was injured, the nature of the injury, and the duration of the absence from work; (2) matches based on pre-injury real wage, expected disability rating, the body part that was injured, the nature of the injury, the duration of the absence from work, age dummies, and educational attainment; and (3) matches based on pre-injury real wage, expected disability rating, the body part that was injured, the nature of the injury, the duration of the absence from work, age dummies, educational attainment, and location dummies.

^aAge dummies used in matching are for 20–29 and 30–39.

^bAge dummies used in matching are for 40–49, 50–59, and 60–64.

^cDoes not include the educational attainment dummies in the matching.

REFERENCES

- Abadie, Alberto, David Drukker, Jane L. Herr, and Guido W. Imbens. 2004. "Implementing Matching Estimators for Average Treatment Effects in Stata." *Stata Journal*, Vol. 4, No. 3 (3rd Quarter), pp. 290–311.
- Abadie, Alberto, and Guido Imbens. 2002. "Simple and Bias-Corrected Matching Estimators for Average Treatment Effects." NBER technical working paper #283.
- Abowd, John M., and David Card. 1987. "Intertemporal Labor Supply and Long-Term Employment Contracts." *American Economic Review*, Vol. 77, No. 1 (March), pp. 50–68.
- Altonji, Joseph G., and Lewis M. Segal. 1996. "Small-Sample Bias in GMM Estimation of Covariance Structures." *Journal of Business and Economic Statistics*, Vol. 14, No. 3 (July), pp. 353–66.
- Baker, Michael. 1997. "Growth Rate Heterogeneity and the Covariance Structure of Life-Cycle Earnings." *Journal of Labor Economics*, Vol. 15, No. 2 (April), pp. 338–75.
- Baker, Michael, and Gary Solon. 2003. "Earnings Dynamics and Inequality among Canadian Men, 1976–1992: Evidence from Longitudinal Income Tax Records." *Journal of Labor Economics*, Vol. 21, No. 2 (April), pp. 289–321.
- Becker, Gary S. 1964. *Human Capital*. New York: Columbia University Press.
- Berkowitz, Monroe, and John F. Burton, Jr. 1987. *Permanent Disability Benefits in Workers' Compensation Benefits*. Kalamazoo, Mich.: Upjohn Institute for Employment Research.
- Boden, Leslie I., and Monica Galizzi. 2003. "Income Losses of Women and Men Injured at Work." *Journal of Human Resources*, Vol. 38, No. 3 (Summer), pp. 722–57.
- Bound, John. 1991. "Self-Reported versus Objective Measures of Health in Retirement Models." *Journal of Human Resources*, Vol. 26, No. 1 (Winter), pp. 106–38.
- Burkhauser, Richard V., John S. Butler, and Robert R. Weathers. 2001. "How Policy Variables Influence the Timing of Applications for Social Security Disability Insurance." *Social Security Bulletin*, Vol. 64, No. 1, pp. 52–83.
- Campolieti, Michele, Morley Gunderson, and Harry Krashinsky. 2006. "Labor Supply Decisions of Disabled Male Workers." *Journal of Labor Research*, forthcoming.
- Charles, Kerwin K. 2003. "The Longitudinal Structure of Earnings Losses among Work-Limited Disabled Workers." *Journal of Human Resources*, Vol. 38, No. 3 (Summer), pp. 618–46.
- Currie, Janet, and Brigitte C. Madrian. 1999. "Health, Health Insurance, and the Labor Market." In Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol. 3C, pp. 3309–3416. Amsterdam: North Holland.
- Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy*, Vol. 80, No. 2 (March), pp. 223–55.
- Hyatt, Douglas E. 1996. "Work Disincentives of Workers' Compensation Permanent Partial Disability Benefits: Evidence for Canada." *Canadian Journal of Economics*, Vol. 29, No. 2 (May), pp. 289–308.
- Newey, Whitney K. 1985. "Generalized Method of Moments Specification Tests." *Journal of Econometrics*, Vol. 29, No. 3 (September), pp. 229–56.
- Weiler, Paul C. 1980. "Reshaping Workers' Compensation for Ontario." A Report Submitted to Robert G. Elgie, Minister of Labour. Toronto: Ministry of Labour.