Intertemporal Labor Supply and Long-term Employment Contracts: Some Evidence from Permanently Disabled Workers

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Abstract

We estimate a two-component model of hours and earnings, derived from the solution to an intertemporal labor supply or contracting model, using data on permanently disabled male workers. This model represents changes in earnings and hours as a portion due to measurement error and the rest due to a nonstationary component that is common to both earnings and hours. Prior work in this area has relied upon measurement error in earnings to identify the impact of changes in productivity on wages and hours, and the key components of the two-factor model. We use data on disabled workers because it includes direct information on a worker's loss of productivity due to injury. This information also allows for new identification strategies with the two-component model. We find that the results from both our estimation strategies are supportive of the intertemporal contracting model.

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1 Introduction

In their work on intertemporal labor supply and long-term contracting, Abowd and Card (1987) used estimates of changes in individual earnings and hours over time within a framework that allowed for a simple test of the two alternative models. If, as in the labor supply model, earnings represent the product of wages and hours, then changes in productivity generate bigger changes in earnings than hours. On other hand, if earnings represent consumption, as in the contracting model, then changes in productivity should generate smaller changes in earnings than hours if leisure is a normal good. Using a sample of workers that never changed jobs, Abowd and Card (1987) found that the contribution of productivity shocks to earnings is greater than that to hours, and so rejected the contracting model. Their estimates of the intertemporal labor supply elasticity for the workers that remained at the same job ranged between 0.3 to 1.8, depending on their data set and model specification. For a sample of workers that changed jobs, the estimates in Abowd and Card (1987) also suggested the contribution of productivity shocks to earnings is greater than that to hours. However, their estimates of the intertemporal labor supply elasticity were much larger, ranging from 2.5 to 52, and not as precisely estimated as in the samples where the workers did not change employers.

We explore these issues in this paper. We use the framework of Abowd and Card (1987), which is a two-component model of changes in earnings and hours that contains a measurement error component as well as a nonstationary component that is common to both earnings and hours. We apply this model to data drawn 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 Ontario workers that had occupational injuries or diseases and resulted in the worker suffering a permanent disability, which impacted their earnings capacity. The occupational accidents that created these disabilities can be viewed as random health shocks that affect the worker's productivity, so unlike previous work in this area, we will be able to incorporate into our framework an observed productivity shock affecting the hours and earnings of these workers. We obtain our estimates with two approaches. First, we use the two-component model of changes in earnings and hours to generate theoretical moment conditions that we fit to the sample moments using a minimum distance estimator. This procedure produces estimates of the key parameters of interest: the intertemporal substitution elasticity and a parameter that describes the sensitivity of consumption decisions to changes in productivity. In addition, since we have estimates of a worker's change in productivity, we can use this information in a multivariate regression of changes in hours and earnings and obtain estimates of the key parameters. We find that there is a remarkable consistency in the results produced by these two approaches, which reject the labor supply model in favor of the intertemporal contracting model.

In the next two sections we provide a discussion of the intertemporal contracting and labor supply models and the econometric specification of the model. We describe our data in Section 4. The empirical results are presented in Section 5 and we conclude the paper with a few summary remarks.

2 Theoretical Framework

We present a general model of earnings and hours under a standard life-cycle labor supply framework. This is the same framework used by Abowd and Card (1987). Individual $i's$ preference in period t for consumption (c_{it}) and labor supply (h_{it}) are modeled as a von Neumann-Morgenstern utility function, and a worker's objective is to maximize the expected discounted value of their lifetime utility

$$\sum_{t=0}^{T}\left(\frac{1}{1+\rho}\right)^{t}\int_{\theta_l}^{\theta_u} u(c_{it}\left(\theta_{it}\right), h_{it}\left(\theta_{it}\right), t)dF_t\left(\theta_{it}\right) \tag{1}$$

where $0<\rho<1$ is a discount factor. Individual marginal productivity in period t is represented by θ_{it}, which is distributed on the interval (θ_l, θ_u) with distribution function $F_t\left(\theta_{it}\right)$. In the intertemporal contracting model the individual maximizes equation (1) subject to the following budget constraint

$$\sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^{t}\int_{\theta_l}^{\theta_u}\left[\theta_{it}h_{it}\left(\theta_{it}\right)-g_{it}\left(\theta_{it}\right)\right]dF_t\left(\theta_{it}\right)=R, \tag{2}$$

where R is training costs for the worker, r is the real interest rate and $g_{it}\left(\theta_{it}\right)$ is an earnings function. Since workers have no access to capital markets in this model $g_{it}\left(\theta_{it}\right)=c_{it}\left(\theta_{it}\right)$. Solving the individual's maximization problem and using a log-linear approximation to the solution of the first order conditions Abowd and Card (1987) obtain the following two equations

$$\log c_{it} = \phi \log \theta_{it} - \alpha \log v_t + a_t, \quad (3)$$

$$\log h_{it} = \eta \log \theta_{it} + \delta \log v_t + b_t, \quad (4)$$

where a_t and b_t are time varying terms that capture shifts in tastes for consumption and leisure and $v_t = \left(\frac{1+\rho}{1+r}\right)^t \lambda$. The parameter ϕ represents the substitution elasticity between consumption and leisure holding the marginal utility of wealth constant, η represents the elasticity of substitution of labor supply across time and different levels of productivity and δ represents the elasticity of labor supply with respect to marginal utility of wealth. If $E(c_{it}) \cong E(\theta_{it} h_{it}(\theta_{it}))$, then Abowd and Card (1987) show that $\eta - \delta \cong \phi$ or

$$\mu \equiv \frac{\phi}{\eta} = 1 - \frac{\delta}{\eta}. \quad (5)$$

The parameter μ, as Abowd and Card (1987) discuss, represents the sensitivity of consumption and hours decisions to changes in productivity. If consumption is more variable than hours after a change in productivity, then $\mu \geq 1$ and leisure is an inferior good. On the other hand, if $\mu < 1$ then changes in productivity influence earnings less than hours. This last point is a testable implication of this intertemporal contracting model.

In the intertemporal labor supply model, the individual still maximizes equation (1), but subject to the following life-cycle budget constraint

$$\sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t \int_{\theta_l}^{\theta_u} \left[\theta_{it} h_{it}(\theta_{it}) - c_{it}(\theta_{it})\right] dF_t(\theta_{it}) = 0. \quad (6)$$

Maximizing equation (1) subject to the budget constraint in equation (6) produces the same first order conditions as the contracting model. However, in the intertemporal labor supply model $g_{it}(\theta_{it}) = \theta_{it} h_{it}(\theta_{it})$. Abowd and Card (1987) show that the first order conditions for the intertemporal labor supply model, using a log-linear approximation, can be written as

$$\log g_{it} = (1+\eta) \log \theta_{it} - \alpha \log v_t + a_t, \quad (7)$$

$$\log h_{it} = \eta \log \theta_{it} + \delta \log v_t + b_t. \quad (8)$$

In the intertemporal labor supply model the variability of hours with respect to earnings, μ, is given by

$$\mu \equiv \frac{(1+\eta)}{\eta}. \quad (9)$$

Abowd and Card (1987) note that since earnings are the product of wages and hours in the intertemporal labor supply model then earnings must respond more than hours to changes in productivity.

3 Econometric Approach

Our first empirical strategy requires fitting the model of earnings and hours implied by the contracting and intertemporal labor supply models to the estimated covariance matrix of earnings and hours. To implement this strategy, Abowd and Card (1987) developed a two-component model of changes in earnings and hours. This specification allowed them to distinguish between the productivity components of earnings and hours from the components of variance associated with preference variation and measurement error. This specification of the model allows for direct estimation of the parameter μ.

The first step in deriving the moment conditions required to estimate the model is to first difference the equations that describe the intertemporal contracting (equations (3) and (4)) and labor supply (equations (7) and (8)) models. The first-differenced versions of equations (3) and (4) for the contracting model, replacing c_{it} with g_{it}, can be written as

$$\Delta \log g_{it} = \phi \Delta \log \theta_{it} - \alpha (\rho - r) + \Delta a_{it} + \Delta u^*_{it}, \tag{10}$$

$$\Delta \log h_{it} = \eta \Delta \log \theta_{it} + \delta (\rho - r) + \Delta b_{it} + \Delta v^*_{it}, \tag{11}$$

where Δu^*_{it} and Δv^*_{it} are random measurement errors. The labor supply model in first-difference form can be written as

$$\Delta \log g_{it} = (1 + \eta) \Delta \log \theta_{it} - \alpha (\rho - r) + \Delta a_{it} + \Delta u^*_{it}, \tag{12}$$

$$\Delta \log h_{it} = \eta \Delta \log \theta_{it} + \delta (\rho - r) + \Delta b_{it} + \Delta v^*_{it}. \tag{13}$$

Abowd and Card (1987) explicitly model individual productivity as

$$\log \theta_{it} = \theta_i + d_t + \xi_\theta x_{it} + \frac{1}{2} \xi_\theta x^2_{it} + z_{it}, \tag{14}$$

where θ_i is the individual-specific component of productivity, d_t is the change in productivity due to an aggregate effect in period-t, x_{it} is experience[1], and z_{it} is a stochastic error term.

[1] Defined as age-education-5.

The first-difference of equation (14) can be written as

$$\Delta \log \theta_{it} = \kappa_{\theta t} + \xi_\theta x_{i0} + \Delta z_{it}, \tag{15}$$

where x_{i0} is the individual's labor market experience at the beginning of the sample period, and $\kappa_{\theta t}$ is a function of time effects.[2]

In addition, Abowd and Card (1987) model preferences for leisure as functions of permanent individual effects, aggregate time effects, and experience effects

$$a_{it} = a_i + a_t + \xi_a x_{it} + \frac{1}{2}\xi_a x_{it}^2 + \varepsilon_{ait}, \tag{16}$$

$$b_{it} = b_i + b_t + \xi_b x_{it} + \frac{1}{2}\xi_b x_{it}^2 + \varepsilon_{bit}. \tag{17}$$

The error terms, ε_{ait} and ε_{bit}, represent transitory deviations in the life-cycle profile of preferences, and are assumed to be independent and identically distributed for all i and t. The first-differences of equations (16) and (17) are

$$\Delta a_{it} = \kappa_{at} + \xi_a x_{i0} + \Delta\varepsilon_{ait}, \tag{18}$$

$$\Delta b_{it} = \kappa_{bt} + \xi_b x_{i0} + \Delta\varepsilon_{bit}. \tag{19}$$

Substituting equations (15), (18) and (19) into equations (10) and (11) and simplifying we can write the earnings and labor supply equations for the contracting model as

$$\Delta \log g_{it} = \kappa_{gt} + \xi_g x_{i0} + \phi\Delta z_{it} + \Delta u_{it}, \tag{20}$$

$$\Delta \log h_{it} = \kappa_{ht} + \xi_h x_{i0} + \eta\Delta z_{it} + \Delta v_{it}, \tag{21}$$

Using equations (15), (18) and (19), we can write the set of equations for changes in earnings and hours for the intertemporal labor supply model as

$$\Delta \log g_{it} = \kappa'_{gt} + \xi'_g x_{i0} + (1+\eta)\Delta z_{it} + \Delta u_{it}, \tag{22}$$

$$\Delta \log h_{it} = \kappa_{ht} + \xi_h x_{i0} + \eta\Delta z_{it} + \Delta v_{it}. \tag{23}$$

As noted by Abowd and Card (1987), the system of equations in either equations (20) and (21) or the pair in equations (22) and (23) provide a two-component model for the changes

[2] Specifically, $\kappa_{\theta t} = \Delta d_t + \xi_\theta - \frac{1}{2}\xi_\theta + \xi_\theta t$, since $x_{it} - x_{i(t-1)} = 1$ and $x_{it}^2 - x_{i(t-1)}^2 = 2x_{i0} + 2t - 1$, where x_{i0} is the labor force experience at the beginning of the sample period.

in earnings and hours. This representation contains a pure measurement error component (Δu_{it} in the earnings equation and Δv_{it} in the hours equation) and a common nonstationary component for both earnings and hours (Δz_{it}).

Moreover, these equations (either (20) and (21) or (22) and (23)) can be used to derive the theoretical formulas for the autocovariances of earnings and hours changes implied by the two-component model. The moment conditions are defined in terms of $\Delta \log \widetilde{h_{it}}$ and $\Delta \log \widetilde{g_{it}}$, which are the deviations of $\Delta \log h_{it}$ and $\Delta \log g_{it}$, respectively, from their regression-adjusted means, given x_{i0} and t (i.e., $\Delta \log \widetilde{g_{it}} = \Delta \log g_{it} - \kappa_{gt} - \xi_g x_{i0}$ and $\Delta \log \widetilde{h_{it}} = \Delta \log h_{it} - \kappa_{ht} - \xi_h x_{i0}$). Since the formulas for the moment conditions are written in terms of μ they can apply to either the contracting or labor supply model. The formulas listed in Table 1 provide the theoretical expressions for the variances and covariances of the changes in hours and earnings as well as the cross-covariances between hours and earnings.

The parameters of interest from this model are estimated by minimizing the following quadratic form

$$(m - f(\Xi))' W^{-1} (m - f(\Xi)), \tag{24}$$

where m is a vector of sample moments, $f(\Xi)$ is a vector of the theoretical moment conditions (from Table 1) and W^{-1} is a weighting matrix.[3] If the estimated variance matrix of second moments (the fourth moment matrix) is selected as the weighting matrix then we have the optimal minimum distance (OMD) estimates of the model's parameters. Alternatively, if we use the identity matrix as the weighting matrix we have the equally weighted minimum distance (EWMD) estimates of the model's parameters. We present parameter estimates obtained using both of these approaches. Abowd and Card (1987) used the OMD estimator to obtain their estimates. However, Altonji and Segal (1996) have pointed out that applying the OMD estimator to covariance structures may result in the estimator having poor small sample properties as well as unstable estimates of the weighting matrix W^{-1}. Because of the potential instability of the OMD estimates we focus on the equally weighted minimum distance estimates. 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)).

Like Abowd and Card (1987), we estimate both stationary and nonstationary MA(2)

[3] Chamberlain (1984) contains a comprehensive discussion of these estimators.

parameterizations of individual productivity changes. If the process is stationary then sample moments used in equation (24) can be the averages (across time) of the elements of the covariance matrix. On the other hand, the nonstationary parameterization requires using the full covariance matrix when minimizing the quadratic form in equation (24).[4]

We also use a multivariate regression to obtain estimates of the model parameters. The permanently disabled workers we study differ from those in typical panel data in that they have all experienced some loss in their earnings capacity. This change in earnings capacity is determined by the Workers' Compensation Board of Ontario when it evaluates the extent of the worker's disability (see the discussion in Section 4). This means that we can rewrite equation (15) as

$$\Delta \log \theta_{it} = \Delta dr_{it} + \kappa_{\theta t} + \xi_{\theta} x_{i0} + \Delta z_{it},$$

where Δdr_{it} is a downward shift in the intercept by the change in earnings capacity and the other variables are as defined previously.[5] We can use this alternative definition of $\Delta \log \theta_{it}$ to define a system of equations that allow us to estimate the effect of a percentage decrease in productivity (Δdr_{it}) on the percentage change in earnings, $\Delta \log g_{it}$, and the percentage change in hours worked, $\Delta \log h_{it}$. This multivariate regression provides a direct estimation strategy that can use the ratio of the coefficients on Δdr_{it} in the earnings and hours equations to test the long-term contracting model against the intertemporal labor-supply model.

4 Data

We use data from the Survey of Ontario Workers with Permanent Impairments (SOWPI) to estimate the model. The SOWPI is a unique data set that was collected by the Ontario Workers' Compensation Board, Canada. In the Ontario workers' compensation system, workers that never fully recover from their injury and suffer some loss in their physical capacity to earn are called *permanently disabled*. Conversely, workers that are injured and suffer no residual impairment are called *temporarily disabled*. The SOWPI surveyed permanently disabled workers who had a physical exam from the Ontario Workers' Compensation

[4]The stationary model has 43 moment conditions, while the nonstationary model has 99 moment conditions.

[5]The intercept term in equation (15) can be rewritten as $\kappa'_{\theta t} = \kappa_{\theta t} + \Delta dr_{it}$.

Board between June 1989 and August 1990. These workers, according to their claims adjudicator and physician, had been deemed to have reached the point of maximum medical improvement. 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.[6] 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 so we had to create an estimate. To do so, we used the regression results in Hyatt (1996), which related actual disability ratings to worker characteristics from the Ontario Workers' Compensation Board's administrative records and different injury classifications.[7] The coefficient estimates from Hyatt's regression were used to create the expected disability rating.

The SOWPI contains just over 11,000 workers who had accidents over a forty-year period and contains retrospective data on the pre- and post-injury employment experiences of these workers. The survey instrument asks retrospective questions about a worker's employment just before he was injured, such as his hours of work per week and hourly wage, as well as demographic information at time-of-injury (gender, marital status, age at time-of-accident), and his employment once he has returned to work after his injury. In addition, there are also retrospective questions about each subsequent post-injury job the worker may have after they returned to work. In particular, workers report initial hours and wages on as many as 5 post-injury jobs in the survey. But since the SOWPI only asks for initial job information, longitudinal information from this survey can only be obtained from job changes.

As previously mentioned, we view the workplace accident that caused the permanent disability as a productivity shock that affects the worker's earning capacity. In particular, since the workers in the survey are all permanently disabled (as defined by the Ontario Workers' Compensation Board) they have all lost some of their capacity to earn. This means that the pre-injury information on each worker is the pre-productivity shock earnings and

[6] Prior to 1990, permanent disability WCB benefits in Ontario WCB were computed using a disability rating schedule (also known as a "meat chart") in which the worker's permanent disability benefits would be equal to their disability rating multiplied by their pre-accident earnings subject to benefit maximums. The worker is entitled to these benefits even if they do not actually experience any losses in earnings.

[7] Specifically, he used data on 34,032 claims, between 1984 and 1989, to estimate his regression.

hours information. After the productivity shock (i.e., the workplace accident) we include the post-injury information on three jobs. The structure of this longitudinal information provides us with data on hours and earnings both before and after the productivity shock. So unlike previous work, we will actually have an exogenous shock that can impact the changes in hours and earnings of these workers.

To perform our minimum distance calculations, it was necessary to use all of the respondent's retrospective reports on their jobs in order to construct sample statistics such as hours and earnings covariances between jobs. For instance, if a worker began his first post-injury job in 1985 and moved to his second post-injury job in 1987, 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- and second-order correlations for wages and hours. We restricted the sample to male workers between the ages of 20 and 64 who had accidents between 1979 and 1984. This sample design produces a short panel that covers 4 jobs, covering about four to six years of calendar time, for 710 males. We also used this panel to estimate the multivariate regressions.

5 Results

We present estimates from the multivariate regression of the change in hours and earnings in Table 2. By taking the ratio of the coefficient estimates on Δdr_{it} from these equations we can obtain an estimate of μ. We present estimates for a pooled sample as well as two subsamples. The second column includes males that were initially reemployed by their time-of-accident employer. The third column of Table 2 includes workers that did not have a post-injury job with their time-of-accident employer. We make the distinction between the second and third columns in our analysis because disabled workers that return to work with their accident employer may receive accommodations, which are arrangements provided by employers to facilitate the employment of disabled persons, and not pay a compensating differential for the accommodations they receive (Gunderson and Hyatt (1996)).[8] On the other hand, workers that do not return to work with the time-of-accident employer pay a com-

[8] Accommodations that may be provided by employers include reduced hours, flexible schedules, light duties or perhaps modifying the worker's workstation or other equipment.

pensating differential for the accommodations that their new employers provide (Gunderson and Hyatt (1996)).

Table 2 shows that the estimates of μ are positive and less than one in magnitude, which is supportive of the contracting model, but the strength of this support is dependent upon the sample used in the analysis. When all workers or workers who return to their pre-injury employer are included in the sample, the estimate of μ is significantly less than one. On the other hand, the estimates of μ from the sample of workers who do not return to their pre-injury employer are much larger in magnitude and not significantly different from one. The evidence from this sample does not reject either the labor supply model or the contracting model. However, this finding is consistent with the displaced worker literature, which has compiled substantial evidence demonstrating that workers who involuntarily leave their workplaces tend to have large wage losses (e.g., Farber (1993)). Workers who return to their pre-injury employers do not lose any firm-specific human capital, whereas those that do not return to their pre-injury employers lose this human capital. Since μ represents the ratio of marginal impact of a decline in productivity on the change in wages with the marginal impact of a decline in productivity on the change in hours, the findings from the displaced worker literature suggest that it is much more likely for μ to be larger for the subsample of workers who do not return to their pre-injury employers. This group will have their post-displacement earnings decreased by their loss in human capital, which is partly caused by their disabling injury. As a result, it is natural to see larger variations in wage losses for this subsample that is attributable to their decrease in productivity.

We present the sample covariance structure for our sample in Table 3. As previously discussed, due to the design of the survey, we do not have data on workers that remained at the same job during the whole study period – all of the workers in our sample have had multiple employers. Like the estimates in Table 2, we present three subsamples for the same reasons (workers that do not return to work with the time-of-accident employer pay a compensating differential for the accommodations that their new employers provide (Gunderson and Hyatt (1996))). The first column of Table 3 presents the pooled sample of all workers. The second column includes males that were initially reemployed by their time-of-accident employer and then had other employers. The third column of Table 3 includes workers that did not have any post-injury jobs with their time-of-accident employers.

The earnings autocovariances in Table 3 indicate that the variance of earnings is greater in the workers that never return to work with their time-of-accident employers. Similarly, the covariance between period t and t-1 earnings is greater in the sample of workers that never returned to work with their accident employers after their injury. The covariance between the change in earnings in period t and earnings in t-2 are smaller than those between period t and t-1. However, as with the other earnings autocovariances, $cov\left(\Delta g_t, \Delta g_{t-2}\right)$ is larger for workers that never returned to their time-of-accident employer. Interestingly, the first-order autocorrelations of earnings are bigger than 0.5 in absolute value in the sample of workers that never return to work with the accident employer and the pooled sample (about -0.92).[9] However, the first-order autocorrelation for earnings is less than 0.5 in absolute value in the sample of workers that at least initially return to their time-of-accident employer.

The autocovariances for hours in Table 3, indicate that the variance of hours for workers that never return to work with their time-of-accident employer are larger than those that do return to their accident employer and then leave. The covariances between hours and lagged hours are quite small, with the one- and two-period lag being slightly larger in the sample that never returned to work with their accident employer. As with the first-order autocorrelations for earnings only the first-order autocorrelation for hours from the sample that initially returns to work with the accident employer is less than 0.5 in absolute value.

The cross-covariances between hours and earnings in Table 3 are quite small. As is the case with the other moments, the cross-covariances between earnings and hours are larger in the sample of workers that never returned to work with their time-of-accident employer. As with the first-order autocorrelations, the ratio of the first-order cross-covariances of earnings and hours to their contemporaneous covariance tend to be bigger than 0.5 in absolute value.

Abowd and Card (1987) noted several conditions under which the parameter μ will be empirically identified, any one of which would be sufficient for identification. Included in these conditions is covariance nonstationarity. We tested for the covariance stationarity of an MA(2) process (see the bottom of Table 3) and rejected the null hypothesis of covariance

[9]Abowd and Card (1989) show that in a pure measurement error model, which excludes the common nonstationary component, the first-order autocorrelations of hours and earnings and the ratio of the first-order cross-covariances of earnings and hours to their contemporaneous covariance is -0.5.

stationarity in all of our subsamples.[10] We also tested whether the data on the changes in earnings and hours represented a nonstationary MA(1) process and rejected this restriction on the data in all of the subsamples we considered.[11] In the empirical work that follows we make the implicit assumption, although we do not test it, that we cannot reject an MA(2) parametrization of the covariances. This is based on Card and Abowd (1987) who could not reject an MA(2) parametrization of the data using the PSID and NLS.[12]

The minimum distance estimates of μ, which represent the relative contribution of productivity shocks to changes in log earnings, and the intertemporal labor supply elasticity, η, are presented in Table 4. Like Tables 2 and 3, we present the estimates for the pooled sample, the subsample that initially returned to work with their accident employer and the subsample that never returned to work with the time-of-accident employer after their injury. Table 4 presents both the equally weighted minimum distance and optimal minimum distance estimates. As we noted earlier, we focus most of the discussion on the equally weighted minimum distance estimates.

The estimates from the stationary model for the subsample that did initially return to work with their time-of-accident employer produces fairly small estimates of μ, with the estimate from the EWMD approach being about 0.05 (and statistically different from zero). The estimate from the OMD approach for the stationary model was about 5 times larger and also statistically different from zero. In both cases we could reject the hypothesis that $\mu = 1$, so changes in hours do not occur at fixed wage intervals. The estimates of μ from the nonstationary model also suggest that μ is quite small. The estimate of μ from the equally weighted minimum distance approach is 0.029 with a standard error of 0.012. The estimate

[10] The alternative conditions that would be sufficient for the empirical identification of μ include second-order serial correlation and first-order correlations of changes in earnings and hours that are less than 0.5 in absolute value. The former of these alternative conditions is not applicable in our study since our panel contains 4 years of data for most individuals. The latter condition is not satisfied in our pooled sample or the sample of workers that never return to their time-of-accident employers because some of the first-order autocorrelations are bigger than 0.5 in absolute value.

[11] A nonstationary MA(1) representation will require that $\text{cov}(\Delta \log g_{it}, \Delta \log g_{it-j}) = 0$, $\text{cov}(\Delta \log h_{it}, \Delta \log h_{it-j}) = 0$, $\text{cov}(\Delta \log g_{it}, \Delta \log h_{it-j}) = 0$ and $\text{cov}(\Delta \log g_{it}, \Delta \log h_{it+j}) = 0$, for $j \geq 2$, with no restrictions on the variances and other covariances.

[12] We are unable to test this assumption because our panel is not long enough to form some of the higher order covariances required to test this parametrization.

of μ using the optimal minimum distance estimate for the nonstationary model is 0.001, but it is not precisely estimated. Like the estimates in the stationary model, we could reject the hypothesis that $\mu = 1$. The EWMD estimates provide support for the contracting model in this subsample. Our estimates differ from those in the multiple employer sample in Abowd and Card (1987), who obtained estimates of μ that were about 1.0 with PSID data and 1.39 with NLS data. Abowd and Card (1987) also obtained estimates larger than 1.0 in their same employer samples, but they were not statistically different from one.

When we estimate the model using the sample of workers that never returned to work with their time-of-accident employer the results are somewhat different. First, the estimates of μ, while still less than 1 in value, are not as precisely estimated. These estimates of μ are also not consistent with the intertemporal labor supply model, which would require estimates of μ bigger than 1. Moreover, the estimates of μ are no longer statistically different from 1, so that we cannot reject the hypothesis that productivity induced changes in hours occur at fixed wage rates. As previously discussed, the difference in μ for these two subsamples of injured workers is consistent with an additional loss in firm-specific human capital for the workers that do not return to their pre-injury employer that accompanies their negative productivity shock due to injury.

The estimates of the intertemporal labor supply elasticity for the stationary and nonstationary model are quite similar. Using the equally weighted minimum distance estimator for the subsample of workers who return to their pre-injury employers, the estimate of η for the stationary model is 0.053 and 0.03 for the nonstationary model. Both of these estimates are also statistically different from zero. When the optimal minimum distance approach is used to estimate the model the estimates of η from the stationary and nonstationary model differ much more (0.316 versus 0.001). Our estimates of the intertemporal elasticity are smaller than the estimates presented in Abowd and Card (1987) for multiple employers as well as the estimates in Abowd and Card (1989), but most of those estimates were not precisely estimated. However, our estimates (particularly, the EWMD) for the sample of workers that initially returned to work with the time-of-accident employer are at the lower range of the estimates of the intertemporal elasticity obtained with instrumental variables estimation strategies, which is approximately 0.0 to 0.5 in Altonji (1986) and MaCurdy (1981).[13] On

[13] See Card (1994) for a review of this literature.

the other hand, some of our results (particularly, those for the workers that never returned to their time-of-accident employer, which are discussed in the next paragraph) are consistent with the estimates in Ham and Reilly (2003), who obtained intertemporal elasticities between 0.5 and 1.5.

The estimates of the intertemporal labor supply elasticities are much larger in the sample of workers that never returned to work with their time-of-accident employer after their injury. For the stationary model the equally weighted minimum distance estimator produces an estimate of η equal to 1.5, which is statistically different from zero at the 5 percent level. When we estimate the nonstationary model, the estimate of η from the EWMD approach increases to 1.87, and it is also statistically different from zero at the 5 percent level. These estimates of the intertemporal elasticity suggest that the component of changes in individual hours attributable to intertemporal substitution effects is fairly large for this group of workers, which suggests that they are likely to have a fairly large change in hours in response to changes in productivity.

The estimates of the elasticity of substitution from the two subsamples present a contrast. The sample of workers that initially return to work with their time-of-accident employers produces elasticity estimates that are consistent with range discussed in Card (1994). On the other hand, the workers that never return to work with their time-of-accident employers have much larger elasticity estimates. This is again consistent with the literature on displaced workers. Farber (1993) demonstrates that involuntarily displaced workers not only have large wage losses, but also have difficulty finding full-time work and, consequently, tend to exhibit large decreases in hours worked after displacement. The relative instability of hours worked by the sample of workers who do not return to their pre-injury employers is striking in comparison with those workers who do return to their pre-accident employers, who have intertemporal labor supply elasticities that are in the low range of those in the earlier existing studies for able-bodied males.

6 Concluding Remarks

We estimated a two-component model of changes in hours and earnings using data on workers who suffered disabilities as a result of occupational injuries. We separated our sample into two subsamples: those that initially returned to work with the time-of-accident employer and those that never returned to work with the time-of-accident employer after reentering the work force. Both subsamples tend to provide little support for the intertemporal labor supply model. Moreover, the conclusions drawn about the two models are much stronger for the evidence from the group of workers who return to their pre-accident employer, since this subsample yields estimates of the parameter μ that are much more precise than those from the sample who do not return to their pre-accident employer. In addition, the estimates of the intertemporal labor supply elasticity are quite large for the sample of workers who do not return to their pre-injury employer. This is consistent with the fact that they are more likely to have fairly large changes in hours in response to changes in productivity caused by a disability. This finding is quite similar to workers without a disability who are displaced from their job.

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Table 1: Theoretical Expressions for the Variances and Covariances of Hours and Earnings

(1)	$var(\Delta \log \tilde{g}_{it})$	=	$\mu^2 var(\Delta \tilde{z}_{it}) + 2\sigma^2_u$
(2)	$var(\Delta \log \tilde{h}_{it})$	=	$var(\Delta \tilde{z}_{it}) + 2\sigma^2_v$
(3)	$cov(\Delta \log \tilde{g}_{it}, \Delta \log \tilde{h}_{it})$	=	$\mu var(\Delta \tilde{z}_{it}) + 2\rho_{uv}\sigma_u\sigma_v$
(4)	$cov(\Delta \log \tilde{g}_{it}, \Delta \log \tilde{g}_{it-1})$	=	$\mu^2 cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-1}) - \sigma^2_u$
(5)	$cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{h}_{it-1})$	=	$cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-1}) - \sigma^2_v$
(6)	$cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{g}_{it-1})$	=	$\mu cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-1}) - \rho_{uv}\sigma_u\sigma_v$
(7)	$cov(\Delta \log \tilde{g}_{it-1}, \Delta \log \tilde{h}_{it})$	=	$\mu cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-1}) - \rho_{uv}\sigma_u\sigma_v$
(8)	$cov(\Delta \log \tilde{g}_{it}, \Delta \log \tilde{g}_{it-2})$	=	$\mu^2 cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-2})$
(9)	$cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{h}_{it-2})$	=	$cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-2})$
(10)	$cov(\Delta \log \tilde{h}_{it}, \Delta \log \tilde{g}_{it-2})$	=	$\mu cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-2})$
(11)	$cov(\Delta \log \tilde{g}_{it}, \Delta \log \tilde{h}_{it-2})$	=	$\mu cov(\Delta \tilde{z}_{it}, \Delta \tilde{z}_{it-2})$

Notes: $\rho_{uv} = corr\ (\Delta u_{it}, \Delta v_{it})$, $\sigma^2_u = var\ (\Delta u_{it})$, $\sigma^2_v = var\ (\Delta v_{it})$,
$\Delta \tilde{z}_{it} = \eta \Delta z_{it}$, $\Delta \log \tilde{g}_{it} = \Delta \log g_{it} - \kappa_{gt} - \xi_g X_{i0}$ and
$\Delta \log \tilde{h}_{it} = \Delta \log h_{it} - \kappa_{ht} - \xi_h X_{i0}$.

Table 2 – Estimated Relative Contribution of Productivity to Earnings and Hours
Simultaneous Equations Approach

	Pooled Sample	**Did Return to Accident Employer at one point**	**Never Returned to Accident Employer**
Coefficient on Disability Rating in Earnings Equation	0.217 (0.086)	0.041 (0.068)	0.562 (0.369)
Coefficient on Disability Rating in Hours Equation (η)	0.293 (0.072)	0.167 (0.057)	0.653 (0.376)
Relative Contribution of Productivity to change in Log Earnings (μ)	0.739 (0.282)	0.243† (0.373)	0.861 (0.679)
Number of Individuals	710	551	159

† denotes that the estimate of μ is significantly different than 1.

This table presents estimates from three samples of workers in the SOWPI who suffered a disability. The "Pooled Sample" in column one consists of all male workers from the SOWPI between the ages of 20 and 64 who had an accident between 1979 and 1984. The group in column two of this table were the subsample of workers who returned to their pre-injury employer at some point after they had recuperated from their injuries, and the group in column three is comprised of the subsample who never returned to their pre-injury employers after recuperating from their injuries. These estimates were derived using a seemingly unrelated regression estimation of the hours and earnings equations in the model. Standard errors are listed in parentheses.

Table 3 – Stationary Covariance Structure
for Permanently Disabled Males from the SOWPI

	Pooled Sample	Did Return to Accident Employer at one point	Never Return to Accident Employer
Earnings Autocovariances			
(1) Var(Δlog g_t)	0.075 (0.036)	0.046 (0.026)	0.191 (0.081)
(2) Cov(Δlog g_t, Δlog g_{t-1})	-0.069 (0.037)	-0.019 (0.004)	-0.176 (0.105)
(3) Cov(Δlog g_t, Δlog g_{t-2})	-0.022 (0.030)	-0.0006 (0.019)	-0.042 (0.169)
Hours Autocovariances			
(4) Var(Δlog h_t)	0.045 (0.032)	0.029 (0.006)	0.117 (0.015)
(5) Cov(Δlog h_t, Δlog h_{t-1})	-0.028 (0.004)	-0.011 (0.006)	-0.073 (0.014)
(6) Cov(Δlog h_t, Δlog h_{t-2})	-0.003 (0.0004)	0.001 (0.001)	-0.027 (0.012)
Cross Covariances			
(7) Cov(Δlog g_t, Δlog h_{t+2})	-0.002 (0.006)	-0.002 (0.004)	-0.002 (0.033)
(8) Cov(Δlog g_t, Δlog h_{t+1})	-0.014 (0.011)	-0.008 (0.005)	-0.030 (0.034)
(9) Cov(Δlog g_t, Δlog h_t)	0.017 (0.010)	0.015 (0.005)	0.032 (0.038)
(10) Cov(Δlog g_t, Δlog h_{t-1})	-0.014 (0.010)	-0.010 (0.006)	-0.025 (0.033)
(11) Cov(Δlog g_t, Δlog h_{t-2})	-0.002 (0.007)	0.0002 (0.003)	-0.021 (0.036)
Specification Tests			
Goodness of Fit for Stationary MA(2)	132.3 {<0.0001}	66.61 {<0.0001}	261.8 {<0.0001}

Goodness of Fit for Nonstationary MA(1)	1,159 {<0.0001}	1,089 {<0.0001}	781.4 {<0.0001}
Number of Individuals	710	551	159

Notes: Standard errors are reported in parentheses, and the p-values for the χ^2 goodness of fit tests are displayed in curly braces. This table presents estimates from three samples of workers in the SOWPI who suffered a disability. The "Pooled Sample" in column one consists of all male workers from the SOWPI between the ages of 20 and 64 who had an accident between 1979 and 1984. Two subsamples of this pooled group were also used. The group in column two of this table were those who returned to their pre-injury employer at some point after they had recuperated from their injuries, and the group in column three is comprised of workers who never returned to their pre-injury employers after recuperating from their injuries. The covariance matrix and standard errors are based on equally weighted minimum distance estimates of the cross-covariances. The test statistic for the stationary MA(2) has 17 degrees of freedom, while the test statistic for the nonstationary MA(1) has 40 degrees of freedom.

Table 4 – Minimum Distance Estimates of Relative Contribution of Productivity to Earnings and Hours

	Pooled Sample		Did Return to Accident Employer at one point		Never Returned to Accident Employer	
	Equally Weighted	Optimally Weighted	Equally Weighted	Optimally Weighted	Equally Weighted	Optimally Weighted
Stationary Model						
Relative Contribution of Productivity to change in Log Earnings (μ)	0.049†	0.289†	0.050†	0.240†	0.600	0.706
	(0.036)	(0.041)	(0.004)	(0.011)	(0.944)	(0.668)
Intertemporal Labor Supply Elasticity (η)	0.052	0.407	0.053	0.316	1.500	2.401
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.765)	(1.920)
Nonstationary Model						
Relative Contribution of Productivity to change in Log Earnings (μ)	0.635	0.331	0.029†	0.001†	0.651	0.440
	(0.860)	(0.371)	(0.012)	(0.037)	(0.379)	(0.456)
Intertemporal Labor Supply Elasticity (η)	1.740	0.495	0.030	0.001	1.865	0.786
	(1.050)	(0.010)	(0.00001)	(0.00003)	(0.559)	(0.055)
Number of Individuals	710		551		159	

Notes: † denotes that the estimate of μ is significantly different than 1. Standard errors are presented in parentheses.
The "Pooled Sample" consists of all male workers from the SOWPI between the ages of 20 and 64 who had an accident between 1979 and 1984. Columns 3 and 4 contain results for those who returned to their pre-injury employer at some point after they had recuperated from their injuries, and the group in the last two columns is comprised of workers who never returned to their pre-injury employers after recuperating from their injuries. "Equally-Weighted" results are derived from an equally-weighted minimum distance procedure, and "Optimally-Weighted" results are derived from an optimally-weighted minimum distance procedure.