Experience and the Wage Elasticity of Labor Supply

Scott T. French and Tess M. Stafford*

August 1 2015

Draft

Abstract

We examine the effect of the presence of learning-by-doing (LBD) on estimates of individuals' intertemporal elasticity of substitution (*IES*). Using a simple model, we show that if wages increase with experience, as evidence suggests, then wages are a function of past labor supply decisions. This violates the exogeneity assumption required for standard estimations, which are based on the responsiveness of labor supply to transitory variation in wages, to be consistent. Using a large data set of the daily labor supply decisions of Florida lobster fishermen, we show that wage elasticity estimates are consistent with a model of labor supply in which work today leads to higher future wages through LBD. We estimate an average bias in the estimated *IES* of 1.6 and a maximal bias of 2.7 associated with ignoring LBD. (JEL D91, E24, J22, J24, J31)

I Introduction

A large literature is devoted to identifying the intertemporal elasticity of substitution (*IES*) in labor supply. By and large, empirical, micro-based studies on this topic assume exogenously given wages and derive small, marginally significant estimates of the *IES*, leading much of the profession to conclude that labor supply elasticities are small.[1] However, evidence suggests that wages increase with work experience, which implies endogenous wage formation.[2] This paper empirically examines the extent to which ignoring this type of endogeneity biases estimates of the *IES* downward.

---

*Department of Economics, The University of New South Wales, Kensington NSW 2052, Australia.
Acknowledgements: Many thanks to Mike Keane, Mike Waldman, and Denzil Fiebig, seminar participants at Resources For the Future, the College of William and Mary, Vanderbilt University, Monash University, and The Australian National University, and conference participants at the 7th Trans-Pacific Labor Seminar.
Corresponding author: t.stafford@unsw.edu.au.

[1] Classic empirical, micro-based studies include MaCurdy (1981), Browning, Deaton and Irish (1985), and Altonji (1986).

[2] See, for example, Mincer (1974), Altug and Miller (1998), Topel (1991), and Hokayem and Ziliak (2014).

When wages grow with work experience, the marginal return to work today is not simply today's wage rate. It also includes the marginal increase in the present value of all future earnings, generated by gaining more work experience today. This implies that labor supply is a function of the total marginal returns to labor, which consist of both today's wage plus these future benefits. When workers experience a temporary increase in the wage, they necessarily experience a temporary increase in total marginal returns, but, as long as future benefits are positive, the percentage increase in total marginal returns will be less than the percentage increase in the wage. As a result, relating wage variation with variation in work hours will produce a downward-biased estimate of the effect of total remuneration on labor supply.

In this paper, we develop a simple model to illustrate the issues associated with estimating the *IES* in the presence of learning-by-doing (LBD). In particular, we show that a standard estimating equation suffers from omitted variable bias by failing to control for the effect of future benefits on labor supply, and standard instrumental variable methods are incapable of correcting for this particular form of bias. To estimate the magnitude of this bias, we employ a large data set of the daily labor supply decisions of Florida lobster fishermen. Our identification strategy is straightforward. As a worker approaches the end of his career, the future benefits of labor supply approach zero.[3] Thus, we identify the *IES* from observations on fishermen who are very close to retirement. Our estimates suggest that the *IES* is relatively large and that the bias in the presence of LBD is significant.

The benchmark model is a standard life-cycle model of consumption and labor supply with a constant *IES*, as in, e.g., MaCurdy (1981), which implies that an agent's labor supply is a log-linear function of the wage and other observable variables and provides the rationale for regression-based estimates of the *IES* using micro-level labor supply data. We then augment the model to allow for human capital accumulation through work experience and

[3]Keane (2011) suggests that the hours response to temporary wages changes for near-retirement workers may also include an income effect, which would invalidate our approach to uncovering the true *IES*. However, this argument is based on a year-to-year changes the wage, whereas we look at daily wage variation and so can reasonably assume a zero-income effect.

show that the labor supply equation of the LBD model contains an extra term that depends on the effect the relative importance of future returns to hours of work today. Based on the insights of the model, we estimate a MaCurdy (1981) type labor supply model on (i) fishermen with zero years of experience in the lobster fishery, (ii) the full population of fishermen, and (iii) fishermen with fifteen or more years of experience that appear close to retirement. Comparing estimates of the *IES* for groups (i) and (iii), then, provides an estimate of the upper bound on the bias associated with ignoring LBD, while comparing the estimated *IES* for groups (ii) and (iii) provides an estimate of the average bias.

Our estimates of the wage elasticity of hours do not vary significantly across groups. However, this is not surprising given that lobster fishermen do not appear to vary their daily hours much at all, with an average wage elasticity of daily hours of only 0.066. Our estimates of the wage elasticity of daily participation, on the other hand, are (i) 0.53, (ii) 1.05, and (iii) 1.76, respectively, from which we conclude that fishermen are quite responsive to daily wage variation and that the bias associated with ignoring LBD is significant – with a true *IES* between 1.6 and 2.7 times the elasticity estimated using traditional methods.

We are not the first to explore the effect of LBD on estimates of the *IES*. Heckman (1976) and Shaw (1989) were among the first to identify this issue. However, Imai and Keane (2004) were the first to estimate the *IES* in a framework consistent with the presence of LBD. In stark contrast to earlier studies that assumed exogenous wages and found small elasticities (in the range of 0 - 0.45), Imai and Keane (2004) report an *IES* estimate of 3.82 using NLSY79 data. To provide further evidence that this result is due to the inclusion of LBD, the authors simulate data based on their fitted LBD model and estimate models that ignore LBD on the simulated data. This exercise produces *IES* estimates in the range of 0.07 - 1.68, suggesting the true elasticity is between 2.3 and 54.6 times larger than what is generated under the assumption of exogenous wages.

Wallenius (2011) conducts a similar exercise. Using cohort data created from the CPS, she estimates the parameters of both an LBD- and a standard-labor supply model, finding that *IES* estimates from the former model are between 1.5 and 5.2 times larger than those associated with the latter model. However, Wallenius (2011) is unable to identify two of the four human capital parameters in the LBD model, namely (i) the depreciation in human capital and (ii) the complementarity between current human capital and labor supply. Instead, she must set values for these parameters and estimate the remaining parameters based on these fixed values. As a result, her estimates of the *IES*, and, therefore, estimates of the bias stemming from ignoring LBD, depend somewhat heavily on her choice of parameter values.

In this paper, we take a simpler approach to estimating the true *IES* and quantifying the bias that requires fewer assumptions. Importantly, generating these estimates does not require making assumptions about the functional form or parameter values of the human capital production function. Our results are similar to those reported in Wallenius (2011) and consistent, though somewhat smaller than, those reported in Imai and Keane (2004).

II Frisch Models of Labor Supply

In this section, we compare two marginal-utility-of-wealth-constant (or Frisch) models of labor supply: a standard model that assumes exogenously given wages and a model that allows for learning-by-doing (LBD) in the wage process.

II.A Benchmark Model

We begin with the standard life-cycle model described in MaCurdy (1981). Agents choose consumption, $C \geq 0$, and leisure, $L \geq 0$, in each period, t, in order to maximize discounted lifetime utility over the working horizon, T,

$$\sum_{t=0}^{T} \frac{1}{(1+\rho)^t} U_{it}[C_{it}, L_{it}] \tag{1}$$

subject to a wealth constraint

$$A_{i0} + \sum_{t=0}^{T} \frac{1}{(1+r)^t} N_{it} W_{it} \geq \sum_{t=0}^{T} \frac{1}{(1+r)^t} C_{it} \tag{2}$$

and a time constraint

$$1 = L_{it} + N_{it}, \text{ for all } t, \tag{3}$$

where the utility function, $U_{it}[\cdot]$, is a twice differentiable function that is increasing in both arguments, ρ is the rate of time preference, A_{i0} is initial wealth, r is the interest rate, N_{it} is hours of work, and W_{it} is the exogenously given hourly wage.[4] Following MaCurdy (1981) and others, we adopt the following CRRA functional form for $U_{it}[\cdot]$

$$\frac{\psi_{it}}{1+1/\eta} C_{it}^{1+1/\eta} - \frac{\zeta_{it}}{1+1/\omega} N_{it}^{1+1/\omega} \tag{4}$$

where ψ and ζ are individual- and time-specific taste shifters and $\eta < -1$ and $\omega > 0$ are individual- and time-invariant parameters that govern the degree of curvature in consumption and labor supply. Note that ω is equal to the intertemporal elasticity of substitution for labor (*IES*).

For $N_{it} > 0$, and assuming perfect foresight, this specification implies that labor supply is given by the following equation:

$$\ln N_{it} = \omega[t \ln(1+\rho) - \ln \zeta_{it} + \ln \lambda_i - t \ln(1+r) + \ln W_{it}] \tag{5}$$

where λ_i is the multiplier on agent i's wealth constraint. Recognizing that $\ln(1+\rho) \approx \rho$ and $\ln(1+r) \approx r$ and assuming that tastes for work are given by $\ln \zeta_{it} = \sigma_i - \mathbf{Z_{it}}\tilde{\boldsymbol{\gamma}} - \tilde{\epsilon}_{it}$, where $\mathbf{Z}$ is observable to the econometrician, but σ and $\tilde{\epsilon}$ are not, we can rewrite the labor supply equation as

$$\ln N_{it} = \alpha_i + \theta t + \mathbf{Z_{it}}\boldsymbol{\gamma} + \omega \ln W_{it} + \epsilon_{it} \tag{6}$$

where $\alpha_i \equiv \omega[\ln \lambda_i - \sigma_i]$, $\theta \equiv \omega(\rho - r)$, $\boldsymbol{\gamma} \equiv \omega\tilde{\boldsymbol{\gamma}}$, and $\epsilon_{it} \equiv \omega\tilde{\epsilon}_{it}$. In this case, the Frisch elasticity of labor supply with respect to the wage is equal to the *IES*:

$$\frac{\partial \ln N_{it}}{\partial \ln W_{it}} = \omega. \tag{7}$$

Although labor supply in any one period depends on wages and labor supply in all other

[4]For simplicity, we assume r is constant across time.

periods, this dependency is captured by λ_i, which is time-invariant. Provided that the researcher has repeated observations on individuals, this dependency can be captured with individual fixed effects. This implies that estimation of the *IES* is quite straightforward, as only the observable, contemporaneous determinants of labor supply are required to identify the parameters of (6), and the estimated value of ω obtained via OLS is a consistent estimate of the IES, provided that exogenous variation in the right-hand-side variables of (6) is observed and free of measurement error.

II.B Learning-By-Doing Model

Suppose, instead, that the period-t wage is a function of past work experience. In particular, let the observed wage be given by

$$W_{it} = \tilde{W}_t K_{it} \tag{8}$$

where K_{it} denotes agent i's human capital in period t, and $\tilde{W}_t$ denotes the return to human capital common to all workers. Assuming human capital is accumulated through work experience – i.e. learning-by-doing – and depreciates at rate δ, then

$$K_{it+1} = (1-\delta)[N_{it} + K_{it}] \tag{9}$$

with $K_{i0} > 0$ for all i.

The addition of LBD in the wage process generates an extra term in (6) so that the labor supply equation is now given by

$$\ln N_{it} = \alpha_i + \theta t + \mathbf{Z_{it}}\boldsymbol{\gamma} + \omega \ln W_{it} + \omega \ln \left[\frac{W_{it} + F_{it}}{W_{it}}\right] + \epsilon_{it}, \tag{10}$$

where

$$F_{it} = \sum_{k=t+1}^{T} \left(\frac{1-\delta}{1+r}\right)^{k-t} \tilde{W}_k N_{ik}. \tag{11}$$

While W_{it} captures period-t marginal returns to period-t labor, F_{it} captures marginal future returns to period-t labor: i.e., the larger is N_{it}, the larger are all future values of K through (9) and, hence, all future wages through (8).

With LBD, the Frisch elasticity of labor supply with respect to the wage is no longer equal to the *IES* but, instead, is given by

$$\frac{\partial \ln N_{it}}{\partial \ln W_{it}} = \omega \left[1 - \frac{F_{it}}{F_{it} + W_{it}} \right]. \tag{12}$$

The wage elasticity is still a function of the *IES*, which captures the effect of total marginal returns to period-t labor, but it is also a function of the relative size of future returns to an additional hour of work, F_{it}, to total remuneration, $W_{it} + F_{it}$. Notice that, as future returns increase relative to period-t returns, the overall wage elasticity becomes smaller. That is, as the effect of current work on future earnings increases, the current wage has less influence on the agent's decision to work today.

Equation (10) differs from (6) by the presence of the second-to-last term in (10), which is determined by the ratio of total remuneration to period-t returns, W_{it}. The presence of this term implies that, in the presence of LBD, an estimation based on (6) will suffer from omitted variable bias. Since, as long as F_{it} is positive, this ratio is mechanically negatively correlated with W_{it}, an estimation based on (6) will infer a value of the *IES* that is biased downward, and the bias will be more severe the more important are future returns to work in total remuneration.

It is also noteworthy that, unlike typical cases of omitted variable bias, because the omitted variable is not simply correlated with the wage, but is a function of it, the bias cannot be corrected via instrumental variables. This is because any exogenous determinant of the wage is necessarily correlated with the disturbance term when the ratio of total to contemporaneous remuneration is omitted.

It is also important to point out that the biased estimate of the *IES* based on (6) is also unlikely to be informative regarding the value of the Frisch elasticity given by (12). First, note that, with LBD, the Frisch elasticity is no longer a constant, but is individual- and time-specific, unlike the biased estimate of the *IES*. Second, even if one was only concerned with estimating an appropriate sample average of the Frisch elasticity, there is no reason to expect the biased estimate of the *IES* to be useful. Both values *are* less than the true *IES* by a magnitude that depends on the relative contribution of contemporaneous to total remuneration to work. However, the average Frisch elasticity is proportional to the average value of $W_{it}/(W_{it} + F_{it})$, while the bias in the *IES* estimate depends on the covariance between the log of this term and all the other regressors in (10). In summary, the presence of LBD implies both that the Frisch elasticity of labor supply with respect to the wage is not equal to the *IES* and that neither the *IES* nor the Frisch elasticity is consistently identified by an estimation that does not control for the effect of future returns to work on labor supply.

Ideally, one would estimate (10) in order to infer the true value of the *IES*. However, this is not generally feasible because the value of future returns to work in period t is not typically observable. Previous studies have attempted to cope with such limitations by specifying and structurally estimating the parameters of a human capital accumulation function simultaneously with the those determining labor supply. However, these methods entail some additional drawbacks. First, the data must contain enough variation to identify all of the structural parameters, which proved difficult in Wallenius (2011). Second, even when estimates of all relevant parameters can be obtained, doing so requires imposing considerable structure on the estimation and employing solution and estimation methods that are computationally taxing, as in the maximum likelihood estimation of the full solution to agents' dynamic programming problem of Imai and Keane (2004).

Instead, we follow a different strategy. Notice that as future returns, F_{it}, become small relative to period-t returns, the second-to-last term in (10) approaches zero and the LBD labor supply equation (10) converges to the benchmark labor supply equation (6). Thus, we propose to estimate (6), but on a group of individuals for whom future returns, F_{it} are negligible, such that the ratio of the total to contemporaneous marginal returns to work is close to zero, and (6) is a reasonable approximation of (10).

To do so, we employ data on the daily labor supply decisions of Florida lobster fishermen, focusing on individuals who are near retirement. In what follows, we argue that LBD is important for workers in this industry but that, for this subsample, the future returns to work are near zero. Further, because our data feature exogenous, observable, daily variation in wages and labor supply decisions, we are able to identify their labor supply elasticity using data over a relatively short period within their life-cycle without having to rely on assumptions regarding the human capital accumulation function.

III Empirical Strategy

In order to provide an estimate of the true *IES* and the bias that is generated by ignoring LBD, we estimate several versions of the following empirical model, based on Stafford (2015), which describes wages, W, hours of work, N, and daily participation:

$$lnW_{it} = \alpha_{wi} + \mathbf{X}_{it}\boldsymbol{\beta} + \mu \ln K_{it} + \epsilon_{wit}, \tag{13}$$

$$lnN_{it} = \alpha_{ni} + \mathbf{Z}_{it}\boldsymbol{\gamma}_n + \delta_n lnW_{it} + \epsilon_{nit}, \text{ and} \tag{14}$$

$$Pr[participation_{it} = 1] = \Phi(\alpha_{pi} + \mathbf{Z}_{it}\boldsymbol{\gamma}_p + \delta_p lnW_{it}), \tag{15}$$

where the subscripts i and t identify fishermen and calendar dates, respectively, and w, n, and p respectively distinguish parameters in the wage, hours, and participation equations.

We provide a brief description of these equations, the variables they contain, and our identification strategy here. The log hours equation, (14), is based on (6), where θt is contained in $\mathbf{Z}_{it}\boldsymbol{\gamma}_n$, and δ_n, rather than ω, is used to denote the coefficient on log wages to highlight the fact that, when (10) is the true model, but (6) is estimated, the coefficient on log wages need not equal ω. The vector of observable taste shifters, $\mathbf{Z}_{it}$, contains temporal variables (season, month, and weekend indicators and interactions of the latter with fisherman age), daily weather variables (current and lagged wind speed and their squares, precipitation, and hurricane activity indicators), and the monthly unemployment rate.

We assume fishermen participate on a given day if utility from fishing, $U(N > 0)$, is greater than utility from not fishing, $U(N = 0)$. Therefore, the probability of participation is $Pr[U(N > 0) - U(N = 0) > 0] = \Phi(\epsilon_{pit})$, where $\Phi(\cdot)$ is the standard normal cdf and ϵ_{pit} is the combined random error component of $[U(N > 0) - U(N = 0)]$. Utility from fishing is not just a function of the daily wage, but also the daily reservation wage. Therefore, the structural participation equation, (15), is a function of the same explanatory variables included in the daily hours equation, (14).[5]

Observed wages are often plagued by self-selection bias, measurement error, and correlation with unobserved variables (even in the absence of LBD). Importantly, these econometric issues have the ability to downward bias estimates of the wage elasticity of labor supply.[6] Furthermore, estimation of (15) requires a wage measure for every possible work opportunity, while we only observe wages for days on which fishermen chose to participate. For these reasons, we use an imputed wage when estimating (14) and (15) in order to address these econometric issues and to generate complete wage records. Imputing wages requires adding structure to the model. In order to introduce (econometric) uncertainty in wages, we modify (8) in the following manner

$$W_{it} = \tilde{W}_{it} K_{it}^{\mu} \tilde{\alpha}_i \tilde{\epsilon}_{it} \tag{7'}$$

where $\tilde{\alpha}_i$ is a time-invariant individual scale parameter and $\tilde{\epsilon}_{it}$ is an idiosyncratic scaler, both of which are known to the worker at the beginning of time, but not to the econometrician. The exponent, μ, on human capital is added to capture the degree to which human capital affects wages. Taking logs and defining $\ln \tilde{W}_{it} \equiv \mathbf{X}_{it}\boldsymbol{\beta}$, $\ln \tilde{\alpha}_i \equiv \alpha_{wi}$, and $\ln \tilde{\epsilon}_{it} \equiv \epsilon_{wit}$, we arrive at (13). The vector of observable earnings shifters, $\mathbf{X}_{it}$, includes temporal variables (season and month indicators), daily weather variables (current and lagged wind speed and their squares, precipitation, and *some* of the hurricane activity indicators), the daily lunar phase, and the monthly unemployment rate.[7] Lastly, we specify K_{it} to be the total number of lobster trips that fisherman i has made during their lifetime prior to the start of season

[5] We follow Kimmel and Kniesner (1998) and Stafford (2015) in modeling participation.

[6] See Oettinger (1999) and Stafford (2015) for empirical evidence and a thorough discussion of these issues.

[7] We assume that earnings do not vary systematically in the days prior to hurricane landfall. Stafford (2015) finds that the evidence supports this assumption.

s.[8] This measure assumes zero depreciation.

As mentioned above, daily hours and wages are only observed on days on which fishermen chose to participate. This non-randomness can create self-selection bias in (13) and (14), which can create poor estimates of $\ln W_{it}$ and produce downward biased estimates of δ_n, even in the absence of LBD. To control for this bias, we estimate type-2 tobit models, which entail jointly estimating the equation of interest and a reduced form probit model of participation via full information maximum likelihood. All variables that affect participation – i.e. the explanatory variables in (13) and (14) – are included as explanatory variables in the reduced form probit model.

Beyond relying on functional form differences, identification of the parameters in (13), (14), and (15) requires that some observables affect labor supply preferences, but not earnings, and vice versa. We assume that weekend indicators, interactions of these variables with fisherman age, and an indicator for whether a hurricane is *anticipated* to make landfall within the next three days affect preferences for work, but not earnings, and thereby identify the selection effect in observed wages. We assume that the lunar cycle affects earnings, but not preferences for work (except through earnings), and thereby identify the wage effect on labor supply.[9]

IV The Florida Spiny Lobster Fishery

In this section, we briefly outline aspects of the Florida spiny lobster fishery and the data that are relevant to our analysis.[10]

IV.A Industry Characteristics

We focus on the daily participation and hours decisions of commercial lobster trap fishermen, virtually all of whom own and operate their own vessel. There are several advantages to

[8]Note that this measure is only employed in the imputation of fishermen's daily wages. Assumptions on the form of the human capital accumulation function are otherwise irrelevant to the estimation of the response of labor supply to daily variation in the wage.

[9]For a thorough discussion of these assumptions and tests of their strength and validity, refer to Stafford (2015).

[10]For more detail, refer to Stafford (2015).

studying this group of fishermen, primarily the availability of data on daily labor supply, earnings, and the key determinants of each.

Earnings are the product of price and catch, both of which vary across time. Prices mainly vary according to global supply and demand and do not exhibit large day-to-day volatility. This is because (i) once cooked and frozen – as is done by dealers at the docks – lobsters are easily storable and transportable and (ii) Florida is typically responsible for only 4-7% of global annual spiny lobster catch. These characteristics tend to smooth the local price and are important to our identification strategy. In particular, we assume that preferences for fishing vary by day-of-week, but that prices and catch rates do not. Since weekend demand can be met with midweek supply (and from any market), there should be no day-of-week price effects. Because the fishermen we study use traps, there should also be no day-of-week catch effects. This is because a trap fisherman's catch on any given day should not depend on the number of other fishermen that choose to participate that day, but only on the number of lobsters that are are already in the fisherman's trap.

Catch rates vary for many reasons and much of this variation is predictable. Lobsters natural cycles make them more abundant in late summer and early fall. Lobsters' preferred habitats are dark enclosed areas, such as reefs. During rough weather, lobsters tend to move from reefs and into traps, so that after strong winds catches are typically higher. During the new moon and when there is cloud cover, lobsters feel safe moving locations since they are less visible to predators. Hence, catch rates are also higher during these periods.

Although the commercial lobster trap fishery is governed by several regulations, none of these regulations significantly restrict individual effort: there are no spatial or temporal quotas on the amount of lobster that can be sold and fishermen are permitted to fish as many days and for as many hours as they wish, provided the season is open and there is daylight.[11] Hence, fishermen have the ability to flexibly respond to variations in earnings

[11] The season is open each year from August 6th to March 31st. There is one constraint on effort. Fishermen must possess a valid permit for each trap they wish to fish. However, there is a liquid market for these permits, enabling fishermen to use as many traps as they wish.

and tastes for work.

IV.B Data

The Florida Fish and Wildlife Conservation Commission (FWC) has provided us with complete marine life sales records for all commercial fishermen that ever sold lobsters between 1986 and 2007. Because it is rare for commercial fishermen to make trips, but have no catch to sell, these records essentially document the complete daily participation histories of all lobster fishermen. Furthermore, these records include the number of hours spent at sea and the fisherman's earnings, thus providing a twenty-two year panel of daily participation, hours, and earnings for the entire population of commercial lobster fishermen active during this period. From this large set of records – which include, for example, shrimp fishermen that sold lobsters on only one occasion – we extract those fishermen that appear to be genuine lobster trap fishermen.

We match daily participation records with (i) a license database that includes the fisherman's age, (ii) daily wind speed data from the National Oceanic and Atmospheric Administration's (NOAA) historical weather buoy database, (iii) daily precipitation data from NOAA's National Climatic Data Center, (iv) daily hurricane activity from historical news and weather articles and (v) the monthly, seasonally-adjusted unemployment rate for the state Florida from the Bureau of Labor Statistics.

Table 1 provides summary statistics on key variables and describes the sample size. Refer to the table notes for a description of how these statistics were calculated. This table illustrates the effect of key variables on earnings and preferences for work, highlighting the strength of our instruments. Panel A demonstrates that participation rates are much lower on Saturdays, Sundays, and on days preceding hurricane activity, indicating strong temporal heterogeneity in preferences for fishing. This is also true of daily hours (Panel B), but effects are small, an observation that we will return to later. Panel C illustrates the strong effect that the lunar phase has on earnings. Earnings are, on average, 25% larger on days surrounding a new moon relative to days surrounding a full moon.

V Empirical Results

Before estimating models of labor supply, we estimate the log wage equation described by (13) on the full sample of lobster fishermen. Parameter estimates from this regression are shown in Table 2. Importantly, log wages are significantly influenced by log experience. This provides strong evidence that the exogeneity assumption underlying estimations based on (10) is violated and that an LBD model of labor supply, is a more appropriate characterization of labor supply. Log wages are also significantly influenced by the moon phase, which supports our use of this as an instrument in identifying the wage elasticity. With these estimates in hand, we generate an uncensored sample of hourly earnings for each individual and each day in the sample, which we argue is free from measurement error, self-selection, and endogeneity concerns.

To provide an estimate of the true *IES*, as well as of the bias generated by ignoring LBD, we estimate (14) and (15) on three different samples. The first sample consists of experienced fishermen that are near retirement. As discussed in Section II.B, for such fishermen, it is reasonable to assume that the second-to-last term in (10) is close to zero. In this case, the bias in the estimated *IES* generated by estimating (6) instead of (10) should be reasonably small. While we observe rich information on experience, we do not observe information on retirement. However, we do observe fisherman age and participation decisions. For the purposes of this analysis, we define "experienced fishermen near retirement" as those that (i) have fifteen or more years of experience in the lobster fishery, (ii) are 60 years of age or older, and (iii) are observed to drop out of the sample before the last observed fishing season and not return. For these fishermen, we keep the last two seasons during which they participated.

The second sample consists of fishermen that are new to the fishery and participating in their first lobster season. According to the theory developed in Section II.B, the second-to-last term in (10) should be largest for this group of fishermen. As a result, estimates of the wage elasticity should be smallest for this group. Comparing elasticities between this group and the experienced group provides an estimate of the maximal bias in the *IES* associated with ignoring LBD. Finally, the third sample is simply the full sample of fishermen, which provides an estimate of the average bias.

Estimates of hours and participation elasticities for these three groups are presented in Table 3. Hours elasticities across all groups are very small and do not exhibit a meaningful pattern. However, there is generally very little variation in daily hours – see, for example, Table 1 – and all estimates in the hours regressions are quite small and often insignificant. Hence, the hours margin does not appear to be an interesting margin to study for lobster trap fishermen. The participation elasticities, however, are relatively large and quite significant. Moreover, the pattern in elasticities across groups is exactly as predicted. Looking at total elasticities, the estimate for high experience fishermen is 2.66 times that of low experience fishermen, suggesting that estimates of the *IES* can include a substantial negative bias when the effect of LBD on the wage process is ignored.

VI Discussion

Like Shaw (1989), Imai and Keane (2004), and Wallenius (2011), our results are consistent with a model of labor supply in which work today leads to higher futures wages through learning-by-doing. Using data on the labor supply decision of Florida lobster fishermen, we find that work experience is an important determinant of the wage and that estimations that ignore this effect result in significantly smaller estimates of the of the *IES*. We estimate that fishermen near retirement, for whom the future returns to work are plausibly near zero, have an *IES* in the range of values typically used to calibrate macroeconomic general equilibrium models, while for new entrants, for whom the model predicts the downward bias due to LBD to be the greatest, the estimated *IES* is much closer to the range typically inferred from microeconometric estimations.

This implies a bias associated with ignoring LBD, which is similar to that reported in Wallenius (2011). Thus, our results, which impose very little structure on the form of LBD, provide support for the effects of LBD inferred by more model-based estimations such as

Imai and Keane (2004). The importance of these findings and those of preceding studies is potentially far reaching. For example, Chang, Gomes and Schorfheide (2002) and Hansen and Imrohoroglu (2009) find that RBC models that incorporate learning-by-doing better fit the data.

References

Altonji, Joseph G. 1986. "Intertemporal Substitution in Labor Supply: Evidence from Micro Data." *Journal of Political Economy*, 94(3): pp. S176–S215.

Altug, Sumru, and Robert A. Miller. 1998. "The Effect of Work Experience on Female Wages and Labour Supply." *Review of Economic Studies*, 65(1): pp. 45–85.

Browning, Martin, Angus Deaton, and Margaret Irish. 1985. "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle." *Econometrica*, 53(3): pp. 503–544.

Chang, Yongsung, Joao F. Gomes, and Frank Schorfheide. 2002. "Learning-by-Doing as a Propagation Mechanism." *The American Economic Review*, 92(5): pp. 1498–1520.

Hansen, Gary D., and Selahattin Imrohoroglu. 2009. "Business Cycle Fluctuations and the Life Cycle: How Important is On-The-Job Skill Accumulation?" *Journal of Economic Theory*, 144(6): pp. 2293–2309.

Hokayem, Charles, and James P. Ziliak. 2014. "Health, Human Capital, and Life Cycle Labor Supply." *American Economic Review: Papers & Proceedings*, 104(5): pp. 127–131.

Imai, Susumu, and Michael P. Keane. 2004. "Intertemporal Labor Supply and Human Capital Accumulation." *International Economic Review*, 45(2): pp. 601–641.

Keane, Michael P. 2011. "Human Capital, Taxes and Labour Supply." *The Economic Record*, 87(SI): pp. 37–44.

Kimmel, Jean, and Thomas J. Kniesner. 1998. "New evidence on labor supply: Employment versus hours elasticities by sex and marital status." *Journal of Monetary Economics*, 42: pp. 289–301.

MaCurdy, Thomas E. 1981. "An Empirical Model of Labor Supply in a Life-Cycle Setting." *Journal of Political Economy*, 89(6): pp. 1059–1085.

Mincer, Jacob. 1974. *Schooling, Experience, and Earnings.* National Bureau of Economic Research.

Oettinger, Gerald S. 1999. "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors." *Journal of Political Economy*, 107(2): pp. 360–392.

Shaw, Kathryn L. 1989. "Life-Cycle Labor Supply with Human Capital Accumulation." *International Economic Review*, 30(2): pp. 431–456.

Stafford, Tess M. 2015. "What Do Fishermen Tell Us That Taxi Drivers Don't? An Empirical Investigation of Labor Supply." *Journal of Labor Economics*, 33(3): pp. 1–24.

Topel, Robert. 1991. "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority." *Journal of Political Economy*, 99(1): pp. 145–176.

Wallenius, Johanna. 2011. "Human Capital Accumulation and the Intertemporal Elasticity of Substitution of Labor: How Large is the Bias?" *Review of Economic Dynamics*, 14(4): pp. 577–591.

Table 1
Summary Statistics on Participation, Hours, and Earnings

	Daily Participation Rate		Average Hours at Sea		Average Hourly Earnings	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
All days	0.261	0.114	8.144	0.322	165.27	52.46
Weekdays	0.287	0.109	8.175	0.301	165.33	51.68
Saturdays	0.244	0.100	8.040	0.316	160.98	50.82
Sundays	0.152	0.082	8.020	0.441	171.45	60.93
Hurricane (prep)	0.079	0.058	8.132	0.586	183.52	77.34
Week of full moon	0.238	0.104	8.081	0.322	147.33	47.34
Week of new moon	0.291	0.123	8.209	0.314	185.08	49.99
Fishermen in sample	965					
Active fishermen on a given day	365.91	49.48				
Open season days in sample	840					
Total lobster trips made	78,914					
Total choice occasions	301,924					

Note.— For each open season day in the sample, I calculate the participation rate (defined as the number of participating fishermen divided by the number of active fishermen), average hours at sea, and average hourly earnings. "Mean" reports weighted averages of these statistics across all days sharing the same characteristic, where daily values are weighted by the number of fishermen participating that day. I classify days as "week of full moon" if they are within three days of the full moon and "week of new moon" if they are within three days of the new moon.

Source.— Adapted from Stafford (2015).

Table 2
Estimates of the Selectivity-Corrected Log Earnings Equation

Variable	Coefficient	Std. Err.	z-statistic
ln(experience)	0.0636	0.0048	13.39
September	-0.1413	0.0124	-11.39
October	-0.2133	0.0175	-12.17
Age	0.0752	0.0044	16.96
Age^2	-0.0005	0.0000	-13.30
Hurricane (land)	-0.0161	0.0740	-0.22
Hurricane (post)	0.0786	0.0747	1.05
Precipitation	0.0247	0.0092	2.70
Wind speed	0.0120	0.0081	1.47
Wind speed^2	-0.0014	0.0007	-1.90
Lagged wind speed	0.0284	0.0069	4.11
Lagged wind speed^2	-0.0004	0.0005	-0.87
Moon phase	-0.3085	0.0172	-17.91
Unemployment rate	-0.0244	0.0271	-0.90
Observations	78,914		

Table 3
Estimates of the Wage Elasticity of Labor Supply

	Low Experience	Full Sample	High Experience
Hours Elasticity	0.174	0.077	0.106
	(0.052)	(0.010)	(0.058)
Participation Elasticity	0.526	1.09	1.754
	(0.327)	(0.105)	(0.418)
Total Elasticity	0.700	1.166	1.860
Fishermen in Sample	240	965	39
Number of Observations	11,838	301,916	3,890