

Returns to Experience and the Elasticity of Labor Supply

SCOTT FRENCH AND TESS STAFFORD*

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Abstract

We use a unique dataset and novel empirical strategy to validate the predictions of labor supply models featuring returns to experience, quantify the bias in standard estimates of the intertemporal elasticity of substitution (IES) that ignore the role of returns to experience, and obtain an unbiased estimate of the IES. Our approach uses the insight that the bias in standard estimates shrinks as returns to experience decline in importance relative to the wage. Using data on the daily labor supply decisions of Florida fishermen, we identify a sample of highly-experienced, near-retirement fishermen, for whom the returns to experience are negligible and standard estimates of the IES are unbiased. We estimate an IES of 2.7, more than twice that of “naive” estimates based on the full sample, and find that the bias is systematically greater for fishermen with greater returns to experience. Our results provide independent evidence consistent with models featuring returns to experience and suggest that the IES is large and that the bias in standard estimates is substantial. (JEL E24, J22, J24, J31)

*Department of Economics, The University of New South Wales, Sydney, NSW 2052, Australia. Corresponding author: t.stafford@unsw.edu.au. Acknowledgements: Many thanks to Evgenia Dechter, Denzil Fiebig, Mike Keane, and Mike Waldman; seminar participants at the University of South Australia, University of Tasmania, Resources For the Future, the College of William and Mary, Vanderbilt University, Monash University, The Australian National University, University of Technology Sydney, Deakin University, University of Sydney, University of Kansas, University of Hawaii, and Macquarie University; and conference participants of the 2016 SOLE annual meeting, the 2016 AMES, and the 7th Trans-Pacific Labor Seminar. We gratefully acknowledge financial support from the University of New South Wales.

1 INTRODUCTION

Substantial evidence suggests that wages increase with work experience.¹ In this case, the marginal return to work is not simply equal to the wage. It also includes the increase in future earnings due to the increase in experience. This wedge between the wage and the marginal return to work has important implications for labor supply behavior. For example, compared to a model in which wages evolve exogenously, workers are less responsive to wage variation, and their responsiveness declines as returns to experience grow. This implies that labor supply elasticities vary across individuals and over the life cycle, which has significant policy implications. The wedge between the wage and the marginal return to work also has important implications for estimation of preference parameters. The intertemporal elasticity of substitution (IES) measures a worker's willingness to substitute hours of work across time periods and determines labor supply elasticities. Because the wage is only a fraction of the returns to an hour of work, relating variation in hours worked to variation in wages produces a downward-biased estimate of the IES. Indeed, many empirical studies following this approach have obtained small, marginally significant estimates of the IES, leading much of the profession to conclude that labor supply elasticities are small.²

In this paper, we use a unique dataset and novel empirical strategy to validate the predictions of labor supply models featuring returns to experience, quantify the bias in standard micro estimates of the IES, and obtain an estimate of the IES that is unbiased under any wage determination process. Our approach is based on the following insights. Using a simple life-cycle model featuring returns to experience, we demonstrate that hours worked obey an otherwise standard labor supply equation with an additional term that is inversely related to the share of the wage in the overall marginal return to work. This result has three key implications. First, estimation of the standard model, which omits this term, suffers from omitted variable bias and produces a downward-biased estimate of the IES. Second, because the omitted variable is mechanically related to the wage, this particular form of bias is present regardless of the relationship between the wage and returns to experience and cannot be corrected by instrumental variables or use of a natural experiment. Third, the smaller is the marginal return to experience relative to the wage, the smaller is the bias.

¹See, for example, Mincer (1974), Topel (1991), Altug and Miller (1998), Hokayem and Ziliak (2014) and Haggag, McManus and Paci (2017) for analyses of the relationship between work experience and the wage.

²MaCurdy (1981), Browning, Deaton and Irish (1985), and Altonji (1986) were early and influential contributions to this literature.

These insights suggest that standard estimation techniques yield plausibly unbiased estimates of the IES when estimation is based on experienced individuals on the verge of retirement, for whom the returns to work experience are negligible. These insights also yield a testable prediction of labor supply models featuring returns to experience: estimates of the IES based on standard techniques will be smallest for workers early in their careers, for whom returns to experience and thus the downward bias are relatively large, and largest for workers near retirement, for whom the bias is relatively small. Finally, comparing unbiased estimates of the IES based on near-retirement individuals with those based on a representative sample of workers provides an estimate of the bias in typical micro estimates of the IES. Notably, our inferences based on these insights do not rely on any particular assumptions about the relationship between labor supply and returns to experience. Our estimation strategy does, however, require observing workers over multiple periods during which the returns to experience are negligible. This is unlikely to be possible when wages are observed on an annual or even a quarterly basis. Instead, we require data on workers who experience high-frequency anticipated or transitory wage variation.

Thus, to test these predictions, estimate the IES, and quantify the bias in standard estimates, we employ a large dataset of the daily labor supply decisions of Florida lobster fishermen and build on the insights and analyses in Stafford (2015). This is an ideal dataset for our purposes for several reasons. First, it features observed daily variation in wages and hours worked for workers who are autonomous and face few constraints on the allocation of their time. Second, a large component of the wage variation is exogenous and predictable because catch rates depend on the lunar cycle. Third, our 22-year panel allows us to identify entry and exit decisions and accurately measure experience, which allows us to identify two key sub-samples: highly experienced fishermen approaching retirement and new entrants to the fishery. Thus, our dataset enables us to identify the IES because we are able to observe sufficient exogenous variation in wages over the short time period before workers' retirement during which returns to experience are plausibly negligible. It also enables us to quantify the typical bias in estimates based on the full sample of fishermen and to test the model prediction that the bias is particularly severe for new entrants. This is not possible using the annual or quarterly panels typically employed in estimation based on micro data.

Our approach complements a growing structural literature that began with Imai and Keane (2004), which fully specifies and estimates rich life-cycle models of consumption, labor supply, and

human capital accumulation.³ Estimation of fully structural models has the advantage of both controlling for the endogeneity of the wage and providing a fully parameterized model that can be used to simulate labor supply elasticities and conduct policy experiments. However, they must specify all relevant features of the wage determination process and labor supply choice environment, including not only the human capital accumulation process but also potentially important considerations such as the tax and transfer system, financial markets, and individuals' labor force participation decisions. This means that such models are necessarily complex, and it may be unclear what moments of the data and modeling assumptions are primarily responsible for identifying the IES. While we cannot simulate counterfactuals, our partially-specified framework allows us to clearly characterize the bias in standard micro estimates of the IES and define a key testable prediction of models that feature returns to experience. Applying these insights to our unique data allows us to validate the predictions of this class of structural models and to obtain an unbiased estimate the IES. To our knowledge our novel empirical approach, applied to our well-suited dataset, is the first to provide an estimate of the IES that is plausibly unbiased in the presence of endogenous wage formation without relying on the specification and joint estimation of the human capital accumulation process.⁴

Our estimates of the IES for total hours worked for our preferred sample of retiring fishermen are between 2.3 and 3.1, and our preferred estimate is 2.7. This is well above typical micro estimates, which tend to lie in the range of 0-0.4.⁵ Our estimate based on the full sample of fishermen is 1.3. Thus, accounting for the bias in standard estimates due to the omission of returns to work experience increases our estimate of the IES by more than a factor of 2. Finally, estimates based on new entrants to the fishery are approximately zero. Thus, our results strongly support the conclusions that returns to experience are an important determinant of labor supply, that workers are quite willing to substitute hours of work across time, and that micro estimates of the IES that ignore returns to experience are significantly biased.

³Heckman (1976) estimated a life-cycle model with human capital but did not model the effect of returns to experience on the labor supply decision. Shaw (1989) estimated the Euler equations of a life-cycle model with learning by doing but did not solve the full model and thus could not calculate point estimates of labor supply elasticities. More recent examples of fully structural estimations include Wallenius (2011) and Keane and Wasi (2016).

⁴Gomme et al. (2004) and Hansen and Imrohroglu (2009) document that aggregate hours are more volatile over the business cycle for both younger and older workers, but they do not use such an insight to infer the value of IES. In fact, doing so using aggregated data would be problematic because, among other issues, macro fluctuations may also be due to other factors that affect the composition of the workforce. To our knowledge, we are the first to identify the IES using micro data on close-to-retirement individuals.

⁵See Keane (2011) for a recent survey of micro estimations.

Our findings regarding both the magnitude of the IES and the size of the bias are within the range found by fully structural estimations that jointly estimate labor supply and the human capital accumulation process, which lends credence to the ability of both approaches to consistently identify the IES. Imai and Keane (2004), Wallenius (2011), and Keane and Wasi (2016) estimate IES values of 3.8, 1.1, and 2. Comparing “true” with “naive” estimates, the calibrated model of Keane (2016) predicts a relative bias factor of “roughly 3.3”, Wallenius (2011) estimates a bias of 2.1, and Imai and Keane (2004) estimate a bias of 3.2 when the naive estimate is based on a simulated sample of working aged men (aged 20–64) and outliers have been removed (see p. 625). Because our results are based on a dataset that has not previously been used to fit a structural model of labor supply and do not rely on assumptions regarding the wage determination process, they constitute new and independent evidence validating the predictions of structural models featuring returns to experience.

Although our estimation controls for any individual or time-varying labor supply shifters, a possible concern is that differences other than the returns to experience cause the fishermen in each sample to respond differently to the predictable, exogenous, daily wage variation in our data. While this concern does not affect identification of the IES in our sample of retiring fishermen, it could imply that the differences in estimates across samples are not driven solely by returns to experience. To check for such a phenomenon, we repeat our estimation using a sample of fishermen who otherwise meet the criteria for inclusion in the sample of retiring fishermen but who are at least two years from retirement. Estimates of the IES for this sample strongly indicate that the differences in elasticity estimates are not driven by differences across cohorts of fishermen in our sample, but are due to differences in returns to experience.

As in Stafford (2015), our estimates of the IES are also robust to a number of additional econometric and modeling issues that have been suggested as sources of bias in standard micro estimates.⁶ Examples of the former include endogeneity of the observed wage due to correlation with tastes for work, measurement error, and sample selection.⁷ Most notably, because hourly earnings in the lobster fishery vary predictably with the lunar cycle, we have a robust instrument for the wage that allows us to control for many forms of endogeneity, which Stafford (2015) shows leads to a

⁶See Keane (2011) for a detailed discussion of the econometric issues and Keane and Rogerson (2015) for a review of potentially important features omitted from standard models.

⁷The problem of measurement error is exacerbated when the wage is computed as the ratio of earnings to hours of work, negatively biasing the wage coefficient.

significantly larger estimate of the IES. Further, the predictable, exogenous, high frequency, and transitory variation in the wage used to identify the IES is more plausibly devoid of income effects than the annual variation in typical labor supply panels.

In addition to returns to work experience, it has been suggested that standard micro estimates may be biased due to the presence of borrowing constraints (Domeij and Floden, 2006), precautionary savings concerns (Low, 2005), and optimization frictions (Chetty, 2012). Unlike standard estimates based on life-cycle variation at annual frequencies, these concerns are unlikely to bias our estimates because we identify the IES from daily variation in the wage and hours worked and because fishermen are autonomous. We discuss the issue of borrowing constraints in more detail in Section 6. Because both our unbiased and our naive estimates of the IES are free from these econometric and modeling concerns, the bias that we observe is truly the remaining bias due to returns to experience and not other causes. This is consistent with the fact that our naive estimate is larger than typical micro estimates of the IES.

In the next section, we present a simple life-cycle labor supply model and demonstrate how returns to work experience causes standard estimates of the IES to be biased. Section 3 describes the key features of the Florida lobster fishery and our dataset. Section 4 explains our empirical strategy for identifying the IES using a sample of highly experienced retiring fishermen. Section 5 presents our empirical results. Section 6 discusses possible alternative explanations of our empirical results, and Section 7 discusses the key implications of our findings.

2 A MODEL OF LABOR SUPPLY WITH LEARNING BY DOING

To demonstrate how returns to experience complicate the estimation of labor supply elasticities, we begin with a standard life-cycle model of consumption and labor supply, as in MaCurdy (1981), extended to allow for learning by doing (LBD) in the determination of the wage. Individuals choose consumption, $c \geq 0$, and hours of work, $h \geq 0$, in each period, t , to maximize lifetime utility over a finite working horizon:

$$U_i = \sum_{t=0}^T \beta^t \left[u(c_{it}, \psi_{it}) - \chi_{it} \frac{h_{it}^{1+1/\omega}}{1+1/\omega} \right],$$

subject to a lifetime budget constraint:

$$A_{i0} + \sum_{t=0}^T R^{-t} [w_{it} h_{it} - c_{it}] \geq 0,$$

where β is the discount factor, ψ_{it} and χ_{it} capture individual- and time-specific tastes for consumption and labor supply, A_{i0} is initial wealth, R is the gross interest rate, and w_{it} is the hourly wage. In this specification, we assume that consumption and labor supply are separable in utility but are agnostic about the form of the consumption sub-utility function. The parameter ω , which governs the degree of curvature in the disutility of labor supply, is the intertemporal elasticity of substitution for labor (IES).

Our main point of departure from MaCurdy (1981) is that we allow the wage to depend on human capital, which is a function of historical work experience. Specifically, we assume that the period- t wage is given by

$$w_{it} = \tilde{w}_{it} k_{it} \quad (1)$$

where k_{it} represents human capital, \tilde{w}_{it} is the marginal return to human capital, and k evolves according to

$$k_{i,t+1} = g(k_{it}, h_{it}, \eta_{it}), \quad (2)$$

where η_{it} is an exogenous shifter of human capital, capturing life-cycle variation in the wage, for example. We assume that $g(\cdot)$ has the following properties: $g_h \geq 0$, $g_k \geq 0$, $g_{kk} \leq 0$, and $g(k, 0, 0) \leq k$. The first two properties imply that human capital is persistent and increasing in work experience. The third ensures that human capital accumulation is not explosive. The final property implies that the stock of human capital (weakly) depreciates over time.

For interior solutions, the individual's intra-temporal first-order condition is given by

$$\chi_{it} h_{it}^{1/\omega} = (\beta R)^{-t} \lambda_i (w_{it} + F_{it}), \quad (3)$$

where λ_i is the multiplier on individual i 's lifetime budget constraint, and F_{it} is given by

$$F_{it} = \frac{g_h(k_{it}, h_{it}, \eta_{it})}{g_k(k_{it}, h_{it}, \eta_{it})} \sum_{s=t+1}^T R^{t-s} \tilde{w}_{is} h_{is}^* \prod_{m=t}^{s-1} g_k(k_{im}, h_{im}, \eta_{im}),$$

for $t < T$, and $F_{iT} = 0$.⁸ The sum $w_{it} + F_{it}$ represents total remuneration for an hour of work, including the wage and the discounted marginal increase in all future earnings due to the additional hour of experience.

⁸The term h^* represents the optimal choice of hours, given by (3). The envelope theorem ensures that a marginal deviation in hours worked in period t does not affect the future returns to work.

Rearranging (3) gives us a log-linear labor supply equation,

$$\ln(h_{it}) = \alpha_i + \theta t + \mathbf{Z}_{it}\boldsymbol{\gamma} + \omega \ln(w_{it}) + \omega \ln\left(1 + \frac{F_{it}}{w_{it}}\right) + \epsilon_{it}, \quad (4)$$

where we define $\alpha_i \equiv \omega \ln \lambda_i + \mu_i$ and $\theta \equiv -\omega \ln(\beta R)$, and we have assumed that $\omega \ln(\chi_{it}) = -(\mathbf{Z}_{it}\boldsymbol{\gamma} + \mu_i + \epsilon_{it})$, where \mathbf{Z}_{it} is a vector of observable variables that affect the individual's tastes for work, and μ_i and ϵ_{it} are individual-specific and i.i.d. shocks, respectively, to tastes for work. These shocks are known to the individual but unobservable to an econometrician.

In this model, the Frisch elasticity of labor supply with respect to the wage (holding constant the marginal utility of wealth, λ_i) is given by

$$\frac{\partial \ln h_{it}}{\partial \ln w_{it}} = \omega \left[\frac{w_{it}}{w_{it} + F_{it}} \right], \quad (5)$$

which is weakly less than ω because $F_{it} \geq 0$ under the assumptions that $g_h > 0$ and $g_k > 0$. The standard model without LBD is the special case in which $g_h = 0$, which implies that $F_{it} = 0$ for all i and t , and (4) reduces to

$$\ln(h_{it}) = \alpha_i + \theta t + \mathbf{Z}_{it}\boldsymbol{\gamma} + \omega \ln(w_{it}) + \epsilon_{it}. \quad (4')$$

In this case, the Frisch elasticity is equal to the IES: $\partial \ln h_{it} / \partial \ln w_{it} = \omega$. In other words, in the standard model, the Frisch elasticity appears as the coefficient on the wage in a simple log-linear labor supply equation. Thus, (4') is the basis of the empirical literature that estimates the Frisch elasticity by regressing individual hours worked on wages, as in MaCurdy (1981).

LBD in the wage process complicates this empirical methodology in two ways. First, it breaks the link between the IES and the Frisch elasticity by breaking the equivalence between the wage and total remuneration for work. Second, as (4) makes clear, estimation based on (4') suffers from omitted variable bias when the wage process is characterized by LBD. As long as F_{it} is non-zero, w_{it} will be negatively correlated with the omitted variable, causing (4') to yield a downward-biased estimate of the IES. The bias will be more severe the more important are future returns to work in total remuneration. Importantly, the omitted variable is mechanically related to the wage, not simply correlated with it, which implies that any exogenous determinant of the wage is necessarily correlated with the disturbance term when the ratio of total remuneration to the wage is omitted. This makes it impossible to correct for this bias using instrumental variables or natural experiments.

While estimation based on (4') will lead to downward-biased estimates of the IES, one might surmise that this biased estimate of ω is informative about the value of the Frisch elasticity, which is also less than ω . This cannot be the case for a couple reasons. First, (5) makes clear that, with LBD, the Frisch elasticity varies across individuals and over time, unlike the biased estimate of ω . Second, even if one wished only to estimate an appropriate sample average of the Frisch elasticity, the average Frisch elasticity depends on the true value of ω and the average value of $w_{it}/(w_{it} + F_{it})$, while the biased estimate of ω depends on the covariance between $\ln(1 + F_{it}/w_{it})$ and all the other regressors in (4). Thus, there is no reason to suspect that the biased estimate of the IES identifies any useful function of the Frisch elasticity. To summarize, in the presence of LBD, 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 (4) to infer the true value of the IES. However, this is not generally feasible because the value of future returns to work is not observable. One way to overcome this obstacle is to specify and structurally estimate a parametric human capital accumulation function simultaneously with the estimation of (4). This approach has the benefit of providing a fully parameterized model that can be used to generate counterfactual predictions, but the imposition of additional structure has some disadvantages. Most notably, estimates of the IES depend on assumptions regarding the form of the human capital accumulation function and other determinants of the wage process. In addition, such models are necessarily complex, meaning that it is not always clear what moments of the data or functional form or distributional assumptions identify the key parameters, and estimating the necessarily large number of parameters reduces the degrees of freedom afforded by the variation in the data.⁹ A fully structural estimation is also often computationally challenging, limiting the dimensions of the choice problem that can be considered.¹⁰

We take a complimentary approach to estimating a full structural model which relies on the following key insight: For individuals whose future returns to work are negligible ($F_{it} \approx 0$), estimation based on (4') is valid, and the IES can be estimated independently from the human capital

⁹This proved a challenge for Wallenius (2011), who had to calibrate certain parameters for identification of the IES to be possible.

¹⁰For example, Imai and Keane (2004) had to develop a novel computational algorithm and use various approximation methods to jointly estimate labor supply and human capital accumulation equations, and only with the latest computing power were Keane and Wasi (2016) able to include features such as an active extensive margin and a realistic tax structure.

accumulation process. In our model, this is the case for individuals at the end of their working lifetime ($t = T$). Thus, we propose to estimate (4') using such individuals.

We employ data on the daily labor supply decisions of Florida lobster fishermen, focusing on highly experienced individuals who are within a few months of retirement. We argue that, while LBD is important for workers in this industry, for this subsample, future returns to work are approximately zero. This is an ideal dataset for this application because it features exogenous, observable, daily variation in wages and because the fishermen make daily labor supply decisions. Because we observe their labor supply decisions at such high frequency, we are able to identify the IES using data over a relatively short period of their life cycle, during which it is reasonable to assume that $F_{it} = 0$. This would not be possible with the annual panels typically used to estimate the IES.

Thus, our empirical strategy and the advantageous features of this dataset allow us to estimate the IES while safely ignoring all other potentially important factors that vary over the life cycle. This is clear from (3), which shows that the dependence of labor supply on consumption, assets, and human capital, as well as wages and hours worked in other periods, is captured by the marginal utility of lifetime wealth, λ_i , which is unlikely to vary over such a short time period and can be controlled for in the estimation by individual fixed effects. This implies that consistent estimation of the IES within our subsample is quite straightforward, and the source of identification is clear, provided that exogenous variation in the right-hand-side variables of (4') is observed and free of measurement error.

3 INDUSTRY BACKGROUND AND DATA

Before fully specifying our empirical model and describing our estimation strategy in detail, we briefly review the key characteristics of the industry we study and the key features of our dataset. More detail is provided in Appendix A and in Stafford (2015).

3.1 Industry Background

We study the labor supply decisions of commercial trap fishermen in the Florida spiny lobster fishery. Virtually all of the fishermen in this industry own and operate a single vessel. At the beginning of each season, participating fishermen drop buoy-marked traps, stamped with their license numbers,

wherever they choose, provided the area is not located within a marine reserve. On each open-season day, fishermen choose whether to pull traps, which traps to pull, and how many to pull. Virtually all fishing trips are single-day trips, so these decisions are repeated on a daily basis. At the end of each working day, fishermen return to port and sell their catches to dealers at spot prices known to fishermen prior to leaving the dock. Fishermen choose when to quit fishing each season and when to exit the fishery entirely.

There are several advantages to studying workers in this industry. First, fishermen are autonomous and face few constraints on labor supply. Although the industry is governed by a number of regulations, none significantly restrict individual effort: there are no spatial, temporal, or individual quotas on the amount of lobsters that can be sold, and fishermen are permitted to fish as many days and for as many hours as they choose, provided the season is open and there is daylight.¹¹ Although most employ one or two crewmen, fishermen unilaterally make labor supply decisions, and crew are expected to be available at all times, including weekends.¹²

Second, earnings vary exogenously from day-to-day, and much of this variation is predictable. Daily earnings are the product of catch and price. Catch rates vary for many reasons. Lobsters' natural cycles make them more abundant in late summer and early fall. Catch rates also vary with the weather and the lunar cycle. Lobsters' preferred habitats are dark enclosed areas, such as reefs and traps. During the new moon, during rough weather, and when there is cloud cover, lobsters are more likely to move locations, because they are less visible to predators, and find their way into traps. Hence, around the new moon or following strong winds or rain, catch rates are typically higher. Prices mainly vary according to global supply and demand and do not exhibit large day-to-day volatility. This is because lobsters are typically cooked and frozen immediately by dealers at the docks, so they are easily storable and transportable, and Florida is typically responsible for only 4-7% of the annual global spiny lobster catch.

Third, we have twenty-two years of data, which enables us to observe many entry and exit decisions and to construct experience measures based on observed participation. This allows us to accurately measure fishermen's levels of experience and identify those fishermen that are new to the

¹¹In addition to these regulations, harvesting lobsters below a minimum size and females with eggs is prohibited, and fishermen must possess both a license to harvest lobsters and a permit for each trap they wish to fish. There is, however, a liquid market for trap permits, enabling fishermen to employ as many traps as they wish.

¹²In circumstances where crew are sick or otherwise unable to work, temporary crew are typically available to fill in.

fishery and those that are near retirement.

Finally, the high frequency labor supply decisions and earnings variation allows us to identify the labor supply elasticity within a very narrow period of time for which we can quite plausibly assume that $F_{it} = 0$.

One potential concern is that trap fishermen’s labor supply has a dynamic component because lobsters accumulate in traps with time. However, this is unlikely to be a major concern. Most fishermen have far more traps than they can pull in a single day. While new lobsters enter traps over time, lobsters in traps are also lost due to escape, predation, or in-trap mortality, and catch per trap stops increasing after some amount of “soak” time. Available evidence suggests that the traps in this industry tend to soak for intervals well beyond the time at which catch per trap peaks or levels off, indicating that, on a given day, a fisherman’s catch depends almost entirely on the prevailing environmental conditions and not on his past fishing activity.¹³

3.2 Data

We employ a dataset of Florida lobster fishermen detailed in Stafford (2015). The dataset contains complete marine life sales records for all commercial fishermen that sold lobsters at any time from the 1986 through the 2007 lobster season, provided by the Florida Fish and Wildlife Conservation Commission (FWC). These records include the number of hours spent at sea, the number of pounds sold of each species, and the price paid per pound for each species, 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.¹⁴ From this large set of records, we use an approach similar to Stafford (2015) to identify those records that appear to be genuine lobster trips, as opposed to trips with lobster by-catch, and those fishermen that appear to be genuine lobster trap fishermen, as opposed to, for example, shrimp fishermen that sold one pound of lobster on one occasion. We drop

¹³A report by Muller et al. (2000) finds no evidence of a positive correlation between catch per trap and soak time in the Florida spiny lobster fishery. In similar fisheries, catch rates were estimated to stop increasing at between 3 and 5 days for American lobster fisheries in New Hampshire and Connecticut (Zhou and Shirley, 1997; Saila, Landers and Geoghegan, 2002), between 1 and 2 days for Eastern rock lobster in New South Wales, Australia (Montgomery, 2005), and between 6 and 12 hours for West Coast rock lobster in South Africa (Loewenthal, Mayfield and Branch, 2000). The average soak time in the Florida spiny lobster fishery varies between 7 and 15 days over the season (Ehrhardt and Deleveaux, 2009).

¹⁴Although sales records have a field to record hours spent at sea, this information is occasionally missing, or “1 day” at sea, rather than a specific number of hours, is recorded. In our preferred sample of fishermen, described below, this occurs on 11% of lobster sales records. We assume that these records are not systematically different from those with valid hours information and simply drop these records from the sample.

from the sample non-lobster trap fishermen, and we classify remaining non-lobster sales records as non-participation in the lobster fishery. This process is documented in Appendix A.

The lobster season opens annually on August 6 and closes on March 31 of the following year. Like Stafford (2015), we restrict our analysis to the first 70 days of each lobster season, when other fisheries in which lobster fishermen often participate are closed. Fishermen are not obligated to remain active in the lobster fishery until the season closes on March 31, and many remove their traps from the ocean prior to this date. Once all traps are removed, fishermen are very unlikely to consider participating in the fishery again that season. Ideally, we would remove from the sample all days after which traps are removed from the ocean because fishermen no longer make participation and hours decisions on these dates. However, these “exit” dates are unobservable. Since commercial fishermen almost always have catch to sell after a trip, like Stafford (2015), we infer a fisherman’s exit date as the last date a sale is made that season, and we drop from the sample all days after this date. Because the vast majority of fishermen continue harvesting lobsters beyond day 70, this exit rule has little effect on our sample in practice: less than 3% of observations are dropped from the sample when this exit rule is applied, and results using samples that include these observations are virtually identical to the results presented here. For seasons in which we observe at least one lobster trip, we assume that fishermen are able to participate on every open-season day prior to their exit date. For seasons in which we do not observe a lobster trip, we assume that fishermen do not make daily participation and hours decisions during that season, and we drop these fishermen-season pairs from the sample.

Our identification strategy relies on selecting a group of individuals for whom returns to experience are negligible. To this end, we select highly experienced individuals close to retiring from the lobster fishery, whom we refer to as “retiring fishermen”. To identify this group, we must determine when fishermen enter and exit the lobster fishery and fishermen’s levels of experience in each observed lobster season.

We do not have information on fishermen prior to 1986 or after 2007, so we can only use the information contained within these years to identify entry and exit decisions and experience levels. For a given fisherman, we define entry as the first season in which we observe a lobster trip, and we define exit as the last season in which we observe a lobster trip. To better ensure that we are not inadvertently capturing re-entry or temporary exits, we drop the first two and last two seasons of

data from our sample. So, for all fishermen remaining in the sample, we observe at least two seasons of non-participation prior to any entry and at least two seasons of non-participation following any exit. We calculate years of experience in the lobster fishery as the number of (observable) lobster seasons in which a fisherman has participated prior to the start of a given season. Given a total of twenty-two seasons of data and that we do not use the last two seasons in the analysis, nineteen years of experience is the maximum observable level at the start of any season. Of course, fishermen observed in the first year of the sample may have more than nineteen years of experience.

We classify a given fisherman in a given season as a “retiring fisherman” if they are at least sixty years of age, they begin the season with at least fifteen years of experience, and they exit the fishery at the end of the season. Using these criteria, our sample of retiring fishermen consists of 50 individuals participating in their last season between 2001 and 2005. We also consider a second sample of retiring fishermen in which we reduce the minimum experience level to ten years. This has the advantage of increasing the sample size to 76 fishermen, but the disadvantage of reducing the likelihood that returns to experience are negligible for this group.

To gauge the bias in estimates of the IES due to ignoring LBD, we estimate elasticities for the full sample of lobster trap fishermen, which can be thought of as “naive” estimates of the IES. To keep our samples as comparable as possible, we restrict our full sample to those fishermen engaged in lobster fishing at any point between 2001 and 2005, the years for which we are able to observe retiring fishermen. Using these criteria, our sample of all fishermen consists of 639 individuals.

To further test the predictions of our model, we also estimate elasticities for a group of individuals for whom returns to experience are expected to be particularly substantial. We hypothesize that new entrants with no experience in the lobster fishery – whom we refer to as “entering fishermen” – belong to this group. We classify a given fisherman in a given season as an “entering fisherman” if they enter the fishery that season and remain in the fishery for at least two seasons after their first season. We apply the second criteria because, if fishermen know that they will exit the fishery soon after they enter, returns to experience may be small even in their first season. As above, we restrict our sample of entering fishermen to those engaged in lobster fishing at any point between 2001 and 2005. Using these criteria, our sample of entering fishermen consists of 29 individuals. We also consider a second sample of entering fishermen in which we reduce the minimum number of observed seasons to two. This has the advantage of increasing the sample size to 40 fishermen,

but the disadvantage of reducing the likelihood that returns to experience are substantial for this group.

To ensure that differences in elasticity estimates across samples are not driven by differences other than the returns to experience that cause the fishermen in each sample to respond differently to the predictable, exogenous, daily wage variation in our data, we also estimate elasticities for a fourth group of fishermen that are very similar to our group of retiring fishermen except that they are not in their final season and so can still benefit from returns to experience. We classify a given fisherman in a given season as a “non-retiring fisherman” if they are at least sixty years of age, they begin the season with at least fifteen years of experience, and they remain in fishery for at least two years after the end of the season. As above, we restrict our sample of non-retiring fishermen to those engaged in lobster fishing at any point between 2001 and 2005. Using these criteria, our sample of non-retiring fishermen consists of 95 individuals. As with retiring fishermen, we also consider a second sample of non-retiring fishermen in which we reduce the minimum experience level to ten years, which increases the sample size to 124 fishermen.

4 EMPIRICAL STRATEGY

In this section, we specify our empirical model of labor supply and our strategy for identifying the IES. Our model predicts that estimates of the IES based on (4') are unbiased only when the sample consists of individuals for whom the returns to experience are negligible and that the bias is more severe the greater are such returns for individuals in the sample. Based on this, we estimate an empirical labor supply model using a sample of highly experienced retiring lobster fishermen. To test the importance of LBD for labor supply behavior and quantify the size of the bias due to ignoring LBD, we compare the estimated IES for this group with estimates based on our full sample of fishermen and a sample consisting of new entrants to the fishery. If LBD leads to downward-biased estimates of the IES, then we expect the estimated elasticity to be greatest for the group of retiring fishermen and smallest for the group of entering fishermen.

The model described in Section 2 assumes an interior solution for hours of work in each period. While this may be a reasonable assumption when considering annual hours worked, the daily labor supply decisions of lobster fishermen feature an active participation choice.¹⁵ To match the empirical

¹⁵Even at annual frequencies, accounting for the extensive margin has been found to be important in estimating

environment, we extend the model to include an extensive margin. We first discuss the specifications for the intensive and extensive margins of labor supply before detailing our empirical strategy for consistently identifying the parameters of interest.

4.1 Intensive Margin

Conditional on fishing, fishermen choose hours of work according to (4). In our empirical approach, we ignore learning by doing and estimate the following version of (4')

$$\ln(h_{it}) = \alpha_i + \mathbf{Z}_{it}\boldsymbol{\gamma} + \delta \ln(w_{it}) + \epsilon_{it}, \quad (6)$$

where α_i is an individual fixed effect, and ω has been replaced with δ to make clear that estimation of (6) will not necessarily yield a consistent estimate of ω unless $F_{it} = 0$. To capture temporal variation in tastes for fishing, \mathbf{Z}_{it} includes indicator variables for each month-by-season, indicator variables for Saturday and Sunday, and interactions of weekend indicators with fisherman age and age squared. The month-by-season indicators also semi-parametrically capture the effect of the difference between the interest and discount rates embodied in θt in (4'). To capture the effect of weather on tastes for fishing, \mathbf{Z}_{it} includes indicator variables for light (10–15 miles per hour), moderate (15–20 mph), and high (20+ mph) average daily wind speed; indicator variables for whether the maximum average daily wind speed during the past five days was light, moderate, or high; daily rainfall; total rainfall during the previous three days; and indicator variables for whether a hurricane is expected to make landfall within the next three days, whether a hurricane is currently ashore, and whether a hurricane made landfall during the past three days. Details on data sources and variable construction are provided in Appendix B.

4.2 Extensive Margin

To allow for an active extensive margin, we extend the model from Section 2 by introducing a daily fixed cost to work, measured in hours (\bar{h}). The lifetime budget constraint becomes

$$A_{i0} + \sum_{t=0}^T R^{-t} [\max\{0, w_{it}(h_{it} - \bar{h}_{it})\} - c_{it}] \geq 0.$$

The time period under consideration, one day, is small relative to an individual's lifetime. This allows us to simplify the individual's extensive margin choice problem in two ways. First, we can

labor supply elasticities. See, e.g., Rogerson and Wallenius (2009) and Erosa, Fuster and Kambourov (2016).

safely ignore the effect on lifetime wealth of the choice of whether to work on a given day. Thus, we can treat λ_i as constant in the individual's participation decision for a given day.¹⁶ Second, this means that a first-order approximation of the future returns to working a given day, which is given by $h_{it}^* F_{it}$, will be highly accurate.¹⁷ Assuming that the error associated with this approximation is negligible, the individual will work if

$$R^{-t} \lambda_i [w_{it}(h_{it}^* - \bar{h}_{it}) + h_{it}^* F_{it}] > \beta^t \chi_{it} \frac{(h_{it}^*)^{1+1/\omega}}{1 + 1/\omega}.$$

In other words, the individual will work on a given day if the total net discounted returns to working h_{it}^* hours, valued at the marginal utility of wealth, is greater than the utility cost of working those hours. Substituting from (3), the individual will work on a given day if

$$\frac{1}{1 + \omega} \left(\frac{\lambda_i}{(\beta R)^t \chi_{it}} \right)^\omega \frac{(w_{it} + F_{it})^{1+\omega}}{w_{it} \bar{h}_{it}} > 1.$$

Rearranging gives the following log-linear condition:

$$\bar{\alpha}_i + \theta t + \mathbf{Z}_{it} \boldsymbol{\gamma} + \bar{\mathbf{Z}}_{it} \bar{\boldsymbol{\gamma}} + \omega \ln(w_{it}) + (1 + \omega) \ln \left(1 + \frac{F_{it}}{w_{it}} \right) + \varepsilon_{it} > 0, \quad (7)$$

for which we have parameterized fixed costs of working by assuming that $\ln(\bar{h}_{it}) = -(\bar{\mathbf{Z}}_{it} \bar{\boldsymbol{\gamma}} + \bar{\mu}_i + \nu_{it})$, where $\bar{\mathbf{Z}}_{it}$ is a vector of observable variables that affect the individual's fixed costs, and $\bar{\mu}_i$ and ν_{it} are individual-specific and i.i.d. shocks, respectively, to fixed costs that are known to the individual but unobservable to an econometrician.¹⁸ In addition, we have defined $\varepsilon_{it} \equiv \epsilon_{it} + \nu_{it}$.

Assuming that ε_{it} is normally distributed implies that the probability that a fisherman participates in the fishery on a given day is given by

$$\Pr(h_{it} > 0) = \Phi \left(\bar{\alpha}_i + \theta t + \mathbf{Z}_{it} \boldsymbol{\gamma} + \bar{\mathbf{Z}}_{it} \bar{\boldsymbol{\gamma}} + \omega \ln(w_{it}) + (1 + \omega) \ln \left(1 + \frac{F_{it}}{w_{it}} \right) \right), \quad (8)$$

where Φ is the standard normal cdf. In principle, (8) can be estimated as a standard binary probit. However, it suffers from the same omitted variable problem as (4), as long as F_{it} is greater than zero and is unobservable. In the same way, as $t \rightarrow T$ or k_{it} becomes large, (8) reduces to

$$\Pr(h_{it} > 0) = \Phi \left(\bar{\alpha}_i + \theta t + \mathbf{Z}_{it} \boldsymbol{\gamma} + \bar{\mathbf{Z}}_{it} \bar{\boldsymbol{\gamma}} + \omega \ln(w_{it}) \right). \quad (8')$$

¹⁶This also allows us to treat the decision of whether to work on a given day as the consideration of a marginal deviation in hours worked, which allows us to continue to apply the envelope theorem, ensuring that the values of h_{it}^* and F_{it} in all periods can be held constant in the individual's decision of whether to work in period t .

¹⁷With fixed costs of working, $F_{it} = \frac{g_h(k_{it}, \bar{h}_{it})}{g_k(k_{it}, \bar{h}_{it})} \sum_{s=t+1}^T R^{t-s} \tilde{w}_{is} \tilde{h}_{is} \prod_{m=t}^{s-1} g_k(k_{im}, \bar{h}_{im})$, where \bar{h}_{it} represents the optimal choice from the set $\{0, h_{it}^* - \bar{h}_{it}\}$. The conditions under which $F_{it} \rightarrow 0$ remain the same.

¹⁸The parameter $\bar{\alpha}_i \equiv \alpha_i + \bar{\mu}_i + \ln \left(\frac{1}{1+\omega} \right) = \omega \ln(\lambda_i) + \mu_i + \bar{\mu}_i + \ln \left(\frac{1}{1+\omega} \right)$.

As with our estimation of labor supply on the intensive margin, in our empirical approach to the extensive margin, we ignore learning by doing, and estimate a version of (8'). We allow for the full set of covariates discussed in Section 4.1 to affect both participation and hours worked. In this case, the probability that a fisherman participates in the fishery on a given day is given by

$$\Pr(h_{it} > 0) = \Phi\left(\tilde{\alpha}_i + \mathbf{Z}_{it}\tilde{\gamma} + \tilde{\delta}\ln(w_{it})\right), \quad (9)$$

where $\tilde{\alpha}_i$ is an individual fixed effect for participation, and $\tilde{\gamma} \equiv \gamma + \bar{\gamma}$. Analogous to (6), ω has been replaced with $\tilde{\delta}$ to make clear that estimation of (9) will not necessarily yield a consistent estimate of ω , and indicator variables for each month-by-season included in \mathbf{Z}_{it} semi-parametrically control for θt in (8').

We are interested in estimating the IES. In our model, in which a period is one day, ω is the IES over hours of work within a working day. However, in most applications, interest lies in the IES over total hours worked over longer time periods – i.e., at quarterly or annual frequencies. Because total hours worked over time periods greater than a day is the product of days worked and hours worked per working day, the total elasticity is the sum of the hours elasticity and the daily participation elasticity. The former is identified by the intensive margin labor supply equation (6) as the estimate of δ , and the latter, defined as the elasticity of the probability of participation on a given day with respect to the wage, is estimated via (9) and given by

$$\frac{\partial \ln \Pr(h_{it} > 0)}{\partial \ln w_{it}} = \tilde{\delta} \frac{\phi\left(\tilde{\alpha}_i + \mathbf{Z}_{it}\tilde{\gamma} + \tilde{\delta}\ln(w_{it})\right)}{\Phi\left(\tilde{\alpha}_i + \mathbf{Z}_{it}\tilde{\gamma} + \tilde{\delta}\ln(w_{it})\right)}, \quad (10)$$

where ϕ denotes the standard normal pdf. When LBD does not affect the labor-supply decision (when $F_{it} = 0$), the sum of these elasticities is equal to the overall Frisch elasticity, which can be compared to standard micro estimates of the Frisch elasticity, and to structural estimates of the IES, based on wage variation over the life cycle.¹⁹

4.3 Estimation

As discussed in Stafford (2015), use of observed hourly earnings to estimate (6) and (9) is problematic for several reasons. First, hourly earnings are determined by dividing daily earnings by daily hours

¹⁹Attanasio et al. (2015) point out that it is conceptually difficult to precisely define a Frisch elasticity of labor supply on the extensive margin. This is not an issue in our context because we can safely assume that the marginal utility of lifetime wealth is unaffected by daily wage variation and the individual's decision of whether to work on a given day.

worked. Given this approach, any measurement error in hours worked will mechanically produce negative correlation between hourly earnings and hours worked. Second, observed hourly earnings may be correlated with unobservables in (6) and (9), even in the absence of LBD. Third, while we only observe earnings when fishermen participate, estimation of (9) requires a measure of earnings for every possible work opportunity.

To address these issues, we follow a procedure similar to Stafford (2015). We estimate (6) and (9) using values of $\ln(w_{it})$ predicted by the following wage-determination equation, which is based on (1):

$$\ln(w_{it}) = \mathbf{X}_{it}\boldsymbol{\beta} + \ln(k_{it}) + v_{it}, \quad (11)$$

where we have assumed that $\ln(\tilde{w}_{it}) \equiv \mathbf{X}_{it}\boldsymbol{\beta} + v_{it}$, \mathbf{X}_{it} is a vector of observable variables that affect hourly earnings, and v_{it} includes measurement error and an i.i.d. shock to hourly earnings that is unobservable to the econometrician. To capture the effect of individual-specific variables on wages, \mathbf{X}_{it} includes individual fixed effects. To capture temporal variation in earnings, \mathbf{X}_{it} includes month-by-season fixed effects. To capture the effect of weather on earnings, \mathbf{X}_{it} includes indicator variables for light, moderate, and high average daily wind speed; indicator variables for whether the maximum average daily wind speed during the past five days was light, moderate, or high; daily rainfall and total rainfall during the previous three days; and indicator variables for whether a hurricane is currently ashore and whether a hurricane made landfall during the past three days. Lastly, \mathbf{X}_{it} includes the daily moon phase, which takes values within the range $(0, 1)$, where 1 denotes a full moon. Details on data sources and variable construction are provided in Appendix B.

The individual and month-by-season fixed effects also flexibly control for k_{it} while allowing us to impose minimal structure on the form of the human capital accumulation process. Because our sample of retiring fishermen includes each individual for only one season, the individual fixed effects are equivalent to individual-by-season fixed effects. Thus, this specification allows each fisherman's stock of human capital at the start of a season to be determined by an arbitrary function of historical variables. It assumes only that daily, individual deviations from a common trend are either statistically independent of the other regressors or of negligible size relative to a fisherman's total stock of human capital at a point in time. The latter is especially plausible for the highly

experience retiring fishermen in our sample.

Identification of the parameters in (6) and (9) requires that some variables affect earnings, but not tastes for or opportunity costs of working. As in Stafford (2015), we assume that the moon phase satisfies this requirement. Fishermen in our sample fish during daylight hours and are not affected by tides. While some fishermen participate in multiple fisheries, which may also be affected by the moon phase, we focus on a portion of each lobster season during which other relevant fisheries are closed. For these reasons, we find it extremely unlikely that the moon phase affects tastes for or opportunity costs of an hour of work.

Because we only observe earnings when fishermen choose to participate, the sample of hourly earnings used to estimate (11) may be nonrandom, which could bias estimates. To correct for possible selection in observed earnings, we estimate a type-2 Tobit model, as termed by Amemiya (1984), which entails jointly estimating (11) and a reduced form probit model of participation via maximum likelihood. All variables that directly or indirectly affect participation – namely \mathbf{X}_{it} and \mathbf{Z}_{it} , which include individual fixed effects – are included as explanatory variables in the reduced form probit model.

Beyond relying on functional form assumptions, identification of selection in (11) requires that some observables affect tastes for or opportunity costs of work, but not earnings. Following Stafford (2015), we assume that weekend indicators, interactions of these variables with fisherman age and age squared, and an indicator for whether a hurricane is expected to make landfall within the next three days satisfy this requirement. For weekend indicators to be valid exclusions, prices and landings must not vary systematically with the day of the week. Because lobsters are easily storable and transportable, demand in one market on a given day can be met with past supply from any market. To test this assumption, Stafford (2015) regresses daily lobster prices on indicators for Saturday and Sunday, season fixed effects, and dealer fixed effects and finds that coefficients on Saturday and Sunday are extremely small and are not significantly different than zero. We find the same in our sample. Landings will be independent of the day of the week provided they are not affected by aggregate participation. This is a reasonable assumption for trap fishermen, since the number of lobsters in one’s trap on any given day should not depend on the number of fishermen participating that day.

For the hurricane preparation indicator to be a valid exclusion, prices and landings must not

be systematically higher or lower on days before a hurricane is expected to make landfall. Clearly, landings cannot be affected by future weather events. The assumption regarding prices would fail if dealers set prices based on the anticipated effect of hurricanes on lobster supply. Because lobsters are easily storable and transportable, any shock to local supply or demand will only have a significant effect on the local price if access to the global market is temporarily impaired. Even in this case, it may not be clear to dealers, a priori, how a hurricane will affect the local market. While a particularly strong storm or a direct hit may damage traps and vessels, leading to lower landings, rough water tends to increase landings. In addition, local demand may fall along with local supply, as evacuation and damage to businesses are likely correlated with damage to traps and vessels. Hence, we would expect any pre-hurricane price effect, if any, to be small. Nevertheless, Stafford (2015) tests this assumption by regressing daily lobster prices on all three hurricane indicators, season fixed effects, and dealer fixed effects and finds that the coefficient on the hurricane preparation indicator is both very small and not significantly different than zero. We find the same in our sample.

Using predicted hourly earnings for each fisherman on each open-season day, we estimate (6) and (9). As with earnings, hours worked are only observed for days on which fishermen choose to participate, which may introduce sample-selection bias in the estimation of (6). To control for this, we estimate a type-2 Tobit model, jointly estimating (6) and a reduced form probit model of participation via maximum likelihood. As with the estimation of (11), all variables that directly or indirectly affect participation – \mathbf{X}_{it} and \mathbf{Z}_{it} , which include individual fixed effects – are included as explanatory variables in the reduced form probit model.

4.4 Summary Statistics

Table 1 provides select summary statistics and demonstrates the effects of key variables on earnings and preferences for work, highlighting the strength of our instruments. Complete summary statistics, including statistics on daily hours worked, are provided in Appendix C. Panel A demonstrates that participation rates are particularly low on Sundays and on days preceding hurricane activity, indicating strong temporal heterogeneity in preferences for fishing. Panel B shows that earnings vary substantially with the moon phase.

Table 1 Summary Statistics on Participation and Earnings

Variable	Retiring		All		Entering		Non-Retiring	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Daily Participation Rates								
All days	0.220	0.194	0.263	0.123	0.192	0.164	0.312	0.161
Weekdays	0.226	0.194	0.291	0.118	0.212	0.168	0.345	0.155
Saturdays	0.223	0.197	0.234	0.110	0.171	0.151	0.266	0.142
Sundays	0.186	0.187	0.155	0.095	0.114	0.123	0.190	0.137
Hurricane preparation	0.152	0.209	0.155	0.151	0.103	0.145	0.155	0.181
Week of full moon	0.186	0.166	0.218	0.105	0.143	0.143	0.257	0.141
Week of new moon	0.265	0.216	0.308	0.127	0.209	0.189	0.350	0.170
Panel B: Average Hourly Earnings								
All days	146.15	78.24	125.92	39.540	91.90	52.99	122.54	44.23
Weekdays	146.23	77.54	125.95	38.520	92.93	49.95	122.12	45.72
Saturdays	149.26	82.07	121.63	39.510	88.56	56.73	118.64	36.74
Sundays	141.75	78.66	132.16	47.450	87.48	72.23	131.97	38.60
Hurricane preparation	152.14	82.60	131.81	45.800	102.77	54.73	114.70	30.74
Week of full moon	115.92	69.05	102.08	22.630	82.95	35.14	99.65	29.15
Week of new moon	176.33	81.44	146.33	46.590	108.35	59.56	143.09	49.39
Panel C: Sample Size								
Fishermen	50		639		29		95	
Lobster trips	654		29,907		350		4,958	
Choice occasions	3,427		125,255		1,965		18,118	

Notes: For each open season day in the sample, we calculate the participation rate as the number of lobster trips taken divided by the number of choice occasions – i.e. the number of fishermen able to participate that day. Panel A provides participation rates averaged over days sharing the same characteristics, such as day of week. Panel B provides hourly earnings averaged across all observations sharing the same characteristics. Thus, days with more participating fishermen carry greater weight in calculating these statistics. “Week of full moon” includes observations within three days of the full moon, and “Week of new moon” includes observations within three days of the new moon. For retiring and entering fishermen, we present summary statistics only for our preferred samples. See Section 3.2 for sample definitions.

5 EMPIRICAL RESULTS

In this section, we present the key results from the estimation of the hours equation (6), the participation equation (9), and the hourly earnings equation (11).

5.1 Evidence on the Returns to Experience

Before presenting our estimates of the IES and assessing the level of bias resulting from ignoring the role of LBD, we present some evidence that LBD is an important determinant of hourly earnings in this industry. While the form and magnitude of the returns to experience have no bearing on our identification of the IES or our test of the theory, it is useful to document that hourly earnings do

appear to rise with experience for the fishermen in our sample. To this end, we estimate two, more restrictive, variations of (11) in which we replace the individual and month-by-season fixed effects used to flexibly control for human capital with functions of experience. In our first specification, we include years of experience, years of experience squared, and an indicator variable that takes the value of 1 in seasons during which a fisherman has one or more years of experience to capture any discrete jump in returns to experience between zero and a positive amount of experience. In our second specification, we include eighteen indicator variables for each possible level of experience. In both specifications, we include all lobster fishermen active between 2001 and 2005, except that we drop from the sample fishermen with lobster sales in the very first season that we observe. It is likely that many of these fishermen participated in the lobster fishery in prior years, so we cannot determine their exact level of experience.

Estimates of the cumulative returns to experience, measured in log earnings per hour, are shown in Figure 1. The solid line represents estimates of the first specification and should be interpreted as the difference in log earnings between the level of experience specified on the x-axis and zero years of experience. The shaded region illustrates the 95% confidence interval of the estimated effect. The results suggest that returns to experience are positive, large, and statistically significant. For example, hourly earnings increase by 22% after accumulating one year of experience and 49% after accumulating five years of experience. The dots (point estimates) and whiskers (95% confidence intervals) represent cumulative returns estimated by the second, semi-parametric specification and are quite similar to the first set of results. Thus, Figure 1 provides strong evidence that earnings are a function of experience, which implies that the exogeneity assumption underlying estimations based on (6) and (9) is violated for all except the end-of-career individuals in our sample. The estimates presented in Figure 1 are based on the full sample of fishermen. To ensure that the estimates are not driven by attrition of low-ability fishermen, we repeat the estimation using a sample of fishermen who go on to obtain 10 or more years of experience. Estimates using this sample are very similar to those reported in Figure 1.

Note that Figure 1 depicts the cumulative returns to experience net of depreciation. Thus, the apparent plateau in cumulative returns to experience for highly experienced fishermen does not imply that the marginal returns to experience approach zero for this group. In fact, significant annual depreciation is quite plausible in this industry (e.g., due to weather events and natural

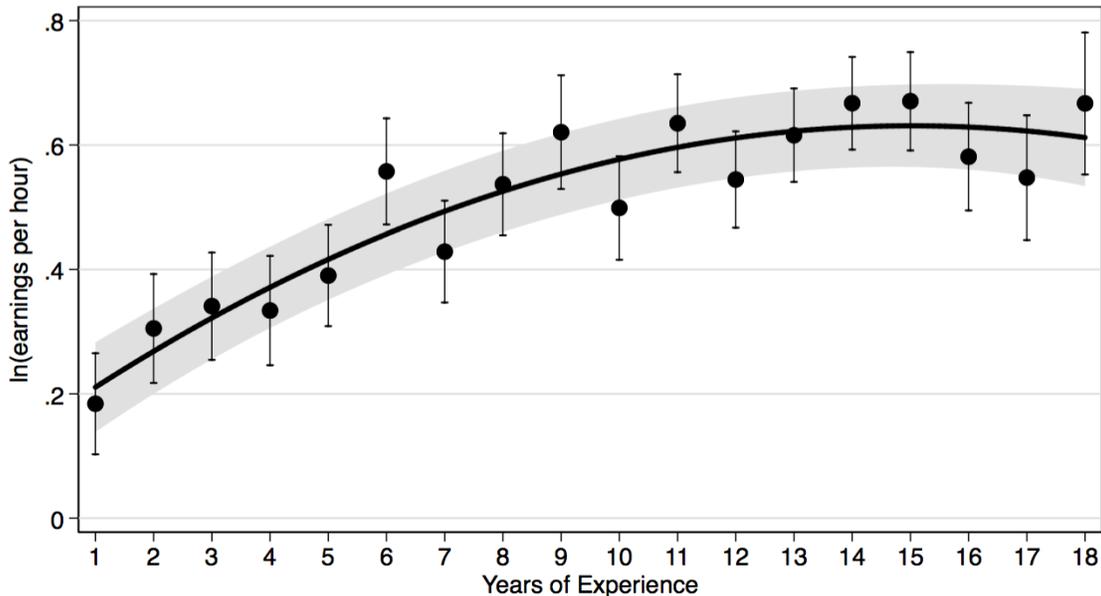


Figure 1 Estimates of the Returns to Experience

Notes: The solid line illustrates the returns to experience based on a specification that includes years of experience, years of experience squared, and an indicator variable that takes the value of 1 in seasons during which a fisherman has one or more years of experience. The gray region illustrates the 95% confidence interval. The dots (point estimates) and whiskers (95% confidence intervals) illustrate returns to experience based on a semi-parametric specification that includes eighteen indicator variables for each possible level of experience (measured in years). For both specifications, estimates should be interpreted relative to the base case of no experience.

migratory patterns that affect the spatial distribution of catch rates), which implies that marginal returns to experience remain non-negligible until a fisherman’s final season before retirement. This highlights the importance of our ability to identify the IES based on individuals who are very close to retirement.

5.2 Baseline Results

In all specifications, we estimate (6) and (9) separately for each sample. In our preferred specification, we also estimate (11) and predict hourly earnings separately for each sample. While we would ideally estimate (11) using the largest possible sample, we take this approach for the following reason. As discussed in Section 4.3, we estimate a selectivity-corrected version of (11) to control for possible selection bias. Based on our model, (6), (9), and (11) are correctly specified and unbiased for our sample of retiring fisherman. However, we know from (7) that estimates of the coefficients of the participation equation will be biased unless the future returns to work are included in the

estimation. This implies that estimates of the coefficients of (6) and (9) for our sample of retiring fishermen may be contaminated by the bias in the selection estimation for (11) if other fishermen are included in the sample.

Table 2 Elasticity Estimates for Retiring, All, and Entering Fishermen

	Retiring Fishermen		All Fishermen	Entering Fishermen	
	15+ Seasons	10+ Seasons		3+ Seasons	2+ Seasons
Panel A: Baseline Specification					
Hours Elasticity	0.249*** (0.062)	0.141*** (0.040)	0.046*** (0.012)	-0.072 (0.150)	0.060 (0.109)
Participation Elasticity	2.401*** (0.548)	1.919*** (0.371)	1.226*** (0.166)	0.004 (1.285)	0.347 (0.874)
Total Elasticity	2.650	2.060	1.272	-0.068	0.407
Panel B: Alternative Specification #1					
Hours Elasticity	0.217*** (0.054)	0.155*** (0.043)	0.046*** (0.012)	-0.035 (0.072)	0.038 (0.070)
Participation Elasticity	2.092*** (0.478)	2.106*** (0.407)	1.226*** (0.166)	0.002 (0.617)	0.220 (0.556)
Total Elasticity	2.309	2.261	1.272	-0.033	0.258
Panel C: Alternative Specification #2					
Hours Elasticity	0.289*** (0.072)	0.184*** (0.051)		-0.046 (0.096)	0.048 (0.088)
Participation Elasticity	2.789*** (0.637)	2.503*** (0.484)		0.002 (0.823)	0.278 (0.701)
Total Elasticity	3.078	2.687		-0.044	0.326
Panel D: Regression Sample Size					
Fishermen	50	76	639	29	40
Lobster trips	654	924	29,907	350	444
Choice occasions	3,327	4,901	122,170	1,938	2,616

Notes: Rows labeled “Hours Elasticity” present estimates of δ from (6). Rows labeled “Participation Elasticity” present estimates of (10) evaluated at covariate sample means. Complete regression results are provided in Appendix D. Rows labeled “Total Elasticity” provide the sum of the hours and participation elasticities and are comparable to estimates of the IES based on annual data. Panels A–C provide estimates based on different methods for predicting log hourly earnings. In Panel A, (11) is estimated separately for each sample. In Panel B, (11) is estimated using the full sample of fishermen. In Panel C, (11) is estimated using a pooled sample of entering and retiring fishermen, where for each sample of retiring fishermen, we pool fishermen with our preferred sample of entering fishermen in the estimation of (11), and for each sample of entering fishermen, we pool fishermen with our preferred sample of retiring fishermen in the estimation of (11). Panel D provides regression sample sizes. Standard errors are clustered by calendar date and are presented in parentheses below point estimates. We do not correct standard errors for the presence of the generated regressor, $\ln(\widehat{w}_{it})$. As in Miles (1997) and Benito (2006), we find it unlikely that this correction would cause the elasticity estimates to become insignificant.

Panel A of Table 2 provides our baseline estimates of the hours and participation elasticities.

Appendix D provides complete regression results for both baseline and alternative specifications. Appendix D also includes the estimates of (11) used to predict hourly earnings, which demonstrate that the moon phase significantly influences earnings; earnings per hour are about 40% higher during a new moon compared to a full moon. Column 1 provides estimates of hours and participation elasticities based on our preferred sample of retiring fishermen, which we argue are unbiased. Both elasticities are positive and statistically significant. Moreover, the sum of these elasticities – which provides a measure of the IES that is comparable to estimates based on annual data – is quite large, suggesting that fishermen are very responsive to variation in the wage. To increase the size of the sample used to estimate the elasticities, we also consider a sample of retiring fishermen in which we reduce the minimum years of experience from fifteen to ten. Column 2 provides estimates based on this sample. The estimates are qualitatively similar and more precisely estimated but somewhat smaller in magnitude.

Column 3 provides estimates based on the full sample of fishermen active between 2001 and 2005. These can be interpreted as “naive” estimates of the labor supply elasticities, based on the assumption that LBD does not affect individuals’ labor supply decisions. This estimation also ignores the presence of k_{it} in (11) because the individual fixed effects do not control for the variation in human capital from season to season given that, in the full sample, we observe fishermen for multiple seasons. Although elasticity estimates remain positive and statistically significant, they are notably smaller. These estimates imply a value of the IES of 1.27. Comparing this with the estimates from column 1 indicates that the presence of LBD in the full sample leads to an estimate of the IES that is biased by more than a factor of 2.

As an additional test of the theory, we estimate labor supply elasticities based on a sample of entering fishermen. Intuitively, and consistent with Figure 1, we expect the returns to experience to be the largest for this group. Thus, the model predicts that the downward bias in the elasticity estimates for this sample to be especially severe. The results are consistent with this prediction. For our preferred sample of entering fishermen, presented in column 4, the point estimate of the IES is approximately zero. The final column presents estimates based on our expanded sample of entering fishermen, which only requires that they participate in the fishery for one additional season after their first. These estimates are also small and not significantly different from zero but are larger in magnitude than those for our preferred sample. This is also consistent with our prediction that the

bias due to LBD is less severe for fishermen who are likely to exit the industry after a short time.

To place these results in context, consider that typical micro estimates of the IES lie in the range of 0–0.4.²⁰ Structural estimations that have jointly estimated labor supply and the human capital accumulation process include Imai and Keane (2004), Wallenius (2011), and Keane and Wasi (2016), which estimate values of the IES of 3.8, 1.1, and 2. Thus, our estimates of the IES lie well within, and somewhat at the high end of, the range found by fully structural estimations, and they are much larger than the range covered by typical micro estimates.

In attempts to quantify the bias due to LBD for standard estimators, both Imai and Keane (2004) and Wallenius (2011) perform “naive” estimations that ignore the role of LBD. The relative bias that we find (2.1) is nearly identical to that found by Wallenius (2011). It is substantially lower than the relative bias of 8–12 found by Imai and Keane (2004). However, their sample consisted of 20 to 36-year-old males, for whom the returns to experience are likely to be relatively high. This is consistent with our finding that the bias is much more severe for the entering fishermen in our sample. When based on a naive estimate of the IES using data simulated for 20 to 64-year-old males and removing outliers from the sample, the relative bias falls to 3.2. Taken together, our results are consistent with the conclusion that the IES is large and that there is substantial bias in estimations that do not account for the role of LBD. The similarity between our point estimates and those of fully structural models lends credence to the ability of both approaches to consistently identify the IES and provides independent validation of the predictions of structural models of labor supply with LBD.

Our estimates of the IES also lie in the range required by representative agent macro models to be consistent with business cycle variation in aggregate hours worked.²¹ We interpret this as evidence in support of the contention of Keane and Rogerson (2012) and others that micro estimates are consistent with large macro elasticities. However, care should be taken in extrapolating any micro estimates of the IES to the macro level. As our model makes clear, the link between the IES and labor supply elasticities is broken in the presence of LBD. Further, aggregate elasticities depend on the response of labor force participation at frequencies much lower than the daily participation decision

²⁰Among highly influential estimates, MaCurdy (1981), Browning, Deaton and Irish (1985), and Altonji (1986) estimate values of 0.1–0.23, 0.14–0.4, and 0–0.35. Keane (2011) surveys the literature and finds an average estimate of 0.3, if one omits MaCurdy (1983), which appears to have been an outlier.

²¹Chetty et al. (2011) summarize this literature, reporting aggregate hours elasticities between 1.9 and 4.

that we estimate.²² Thus, while our empirical approach is capable of consistently identifying the IES, a fully structural model is still needed to predict labor supply responses to changes in earnings across the life cycle and to aggregate individual responses to macro-level elasticities.

5.3 Alternative Specifications

While we prefer to estimate (11) separately for each sample for the reasons cited above, this does allow the estimated effect of the moon phase on hourly earnings to vary across samples. Because this is the key instrument responsible for identifying the IES, this could induce differences in estimates across the samples apart from any bias due to LBD. As a check for whether this is a significant driver of the differences in the estimates presented in Panel A of Table 2, we consider two alternative estimations of (11) that use pooled samples of fishermen.

In the first, we use the predicted earnings based on the full sample of fishermen, which underlie the estimates in column 3 of Panel A. These results, summarized in Panel B, are qualitatively similar to the baseline results. The estimate of the IES from our preferred sample falls slightly, consistent with the fact that the coefficient on the moon phase is somewhat larger in absolute value for the full sample estimation of (11).²³ Nevertheless, these results continue to support the overall message that the estimated IES appears to be biased downward when LBD is not properly accounted for, and the estimates for the sample of entering fishermen remain small and statistically insignificant. We stress that these estimates are potentially susceptible to bias because of the failure to control for LBD in the selection estimation for (11). However, these results make clear that the difference in the estimated IES between the sample of retiring fishermen and the other samples is not a result of differences in the prediction of wages across samples but is due to differences in the fishermen’s responses to exogenous wage variation, as our model predicts.

In the second alternative specification, we pool our samples of entering and retiring fishermen in the estimation of (11). To ameliorate concerns of bias in the selection equation contaminating the estimation of (6) and (9) for the retiring fishermen, in the selection estimation for (11), we interact every variable contained in \mathbf{X}_{it} and \mathbf{Z}_{it} with an indicator variable equaling one if the individual is an entering fisherman. Compared to the full sample estimation, this specification produces an estimate of the IES for the sample of retiring fishermen that is plausibly unbiased while continuing to impose

²²See, e.g., Rogerson and Wallenius (2009), Erosa, Fuster and Kambourov (2016), and Attanasio et al. (2015).

²³See Appendix Tables D1 and D2.

a constant effect of the moon phase on hourly earnings for entering and retiring fishermen. However, because it only includes these two samples of fishermen, it does not yield elasticity estimates for the full sample.²⁴

The results for this specification are summarized in Panel C of Table 2. Again, the estimates are qualitatively similar to those in Panel A. In this case, however, the estimates of the IES for both samples of retiring fishermen are somewhat larger than the baseline results. Again, this reflects the differences in the estimated coefficient on the moon phase in the hourly earnings estimation.

We claim that differences in elasticity estimates across samples are due to differences in returns to experience. However, individuals in these samples may differ in other ways, and there may be concern that these differences somehow influence our results. It should be noted that because our elasticity estimates are identified by daily variation in the moon phase, any factors that shift an individual’s labor supply or that may be correlated with the wage or tastes for work but not with the lunar cycle are not a concern. In addition, the effect of the moon phase on catch rates is well-known in this and other fisheries, even among recreational fishermen, and the moon cycle is extremely predictable and salient information to all fishermen. Therefore, even inexperienced fishermen are able to predict, and respond to, the wage variation driven by the lunar cycle. Thus, it is only factors that make individuals in the different samples respond differently to this predictable, exogenous, daily variation in the wage that may influence our results. For example, our results could be affected if there were heterogeneity in the IES across individuals along with a higher rate of attrition for low-IES fishermen.

To address this possibility, we compare elasticity estimates of retiring fishermen with those of our sample of “non-retiring fisherman” – those who meet the same age and experience criteria as the retiring fishermen but who are at least two years from retirement. Thus, while fishermen in these samples differ in terms of returns to experience, they are very similar in terms of age and career histories. Table 3 provides elasticity estimates based on these samples. As our model predicts, because returns to experience are non-negligible for non-retiring fishermen, the elasticity estimates for these fishermen are notably smaller than the estimates for retiring fishermen. These results strongly suggest that the differences in elasticity estimates observed in Table 2 are, in fact, due to

²⁴We do not estimate the analogous specification for the full sample because the large number of interaction terms makes estimation of the reduced-form probit model computationally impractical.

Table 3 Elasticity Estimates for Retiring and Non-Retiring Fishermen

	Retiring Fishermen		Non-Retiring Fishermen	
	15+ Seasons	10+ Seasons	15+ Seasons	10+ Seasons
Panel A: Alternative Specification #1				
Hours Elasticity	0.217*** (0.054)	0.155*** (0.043)	0.034* (0.019)	0.046*** (0.017)
Participation Elasticity	2.092*** (0.478)	2.106*** (0.407)	1.186*** (0.234)	1.338*** (0.218)
Total Elasticity	2.309	2.261	1.220	1.384
Panel B: Alternative Specification #2				
Hours Elasticity	0.210*** (0.053)	0.153*** (0.043)	0.033* (0.019)	0.045*** (0.017)
Participation Elasticity	2.024*** (0.462)	2.086*** (0.403)	1.147*** (0.226)	1.325*** (0.216)
Total Elasticity	2.234	2.239	1.180	1.370
Panel C: Regression Sample Size				
Fishermen	50	76	95	124
Lobster trips	654	924	4,958	6,314
Choice occasions	3,327	4,901	17,427	24,063

Notes: See Table 2. Complete regression results are provided in Appendix D. Panels A and B provide estimates based on different methods for predicting log hourly earnings. In Panel A, (11) is estimated using the full sample of fishermen. In Panel B, (11) is estimated using a pooled sample of retiring and non-retiring fishermen, where fishermen with fifteen years of experience or more are pooled together, and fishermen with ten years of experience or more are pooled together. Because our sample of non-retiring fishermen includes more than one season per fisherman, we include individual-by-season fixed effects in our estimations of (6), (9), and (11). To ameliorate concerns of bias in the selection equation for (11), we interact every variable contained in \mathbf{X}_{it} and \mathbf{Z}_{it} with an indicator variable equaling one if the individual is a retiring fisherman.

differences in returns to experience and not due to other differences across cohorts of fishermen.

6 ALTERNATIVE EXPLANATIONS

In this section, we discuss two alternative models of labor supply that also predict a positive correlation between labor supply elasticities and experience and argue that these models do not explain our findings.

6.1 Borrowing Constraints

Domeij and Floden (2006) demonstrate that estimates of the intertemporal elasticity of substitution can be biased downward if the econometrician ignores binding borrowing constraints. A worker whose borrowing constraint is binding must finance present consumption with current labor income.

As a result, the worker can only smooth consumption by working relatively more hours in periods when wages are low than would a worker who can borrow in low-wage periods. When credit constraints are binding, but ignored, the econometrician may mistakenly attribute non-responsiveness to variations in the wage to a low desire to intertemporally substitute labor hours, biasing estimates of the IES downward. In econometric terms, the problem is that the wage is negatively correlated with the unobservable marginal utility of borrowing.

While one may surmise that credit constraints could explain the difference in elasticity estimates between retiring and other fishermen if retiring fishermen are less likely to be credit constrained, we do not think that credit constraints are a significant concern in our setting. This is because, unlike Domeij and Floden (2006), we focus on *daily* labor supply decisions attributable to predictable wage variation. It is important to note that the econometric problem due to occasionally binding borrowing constraints arises only if the marginal utility of borrowing is correlated with the wage. This is likely the case for quarterly or annual average wages over the life cycle. However, we argue that any such correlation between day-to-day changes in the marginal utility of borrowing and moon-driven changes in the wage over relatively short time horizons is negligible. This is because such changes in daily wages induce negligible changes in fishermen's total wealth on any given day.

Put differently, in order for credit constraints to explain a significant portion of our findings, it would have to be the case that a substantial share of non-retiring fishermen are truly hand-to-mouth consumers who rely on their daily landings to fund their consumption at the end of each day. We find it extremely unlikely that the fishermen in our sample would have no access to consumer credit or sufficient cash or other liquid assets to cover day-to-day purchases in the week or so around the full moon when earnings are below average.²⁵ Further, credit constraints may bind intermittently within our sample period due to other phenomena, such as health shocks, but this is not a concern unless such shocks are correlated with the lunar cycle.

It is worth noting that borrowing constraints affect labor supply through a fundamentally different channel than LBD. Whereas LBD directly affects the marginal return to an hour of work, the marginal utility of borrowing enters the intra-temporal labor supply equation indirectly through its

²⁵Domeij and Floden (2006) assume a single asset that can be accessed annually. For our setting, we find it more appropriate to consider a model with at least two assets: a long-term asset, analogous to that of Domeij and Floden (2006), and a short-term asset embodying instruments such as cash and bank balances, credit cards, payday loans, and informal loans to and from friends and family. The constraint on the latter must bind when wages are temporarily low in the days around the full moon for our results to be affected.

effect on the marginal utility of wealth, λ_i . Therefore, borrowing constraints will bias estimates of the IES in our setting only if they induce significant variation in the level of λ_i from day to day. By contrast, the future returns to an hour of work need only be non-negligible relative to the hourly wage for LBD to significantly bias estimates of the IES.

6.2 Reference Dependence

Beginning with Camerer et al. (1997), a literature has developed exploring the role of reference dependence in labor supply. A particular form of reference dependence that has been studied extensively suggests that workers base decisions, at least in part, on daily income targets. Workers are loss averse in that the loss in utility from falling short of the target income is greater than the gain in utility from exceeding the target income by the same amount. This kink in the utility function implies that, over a range of wages, individuals will find it optimal to work just as much as is necessary to earn their target income, which means that a portion of a reference-dependent worker's labor supply curve is "backward-bending". For this reason, estimates of the IES based on the standard model will be biased downward if workers are reference dependent. The greater is loss aversion, the greater is the portion of the labor supply curve that is backward bending, and the greater is the bias in estimates of the IES.

Averaged over a long enough period, loss averse workers earn less per hour than neoclassical workers. For this reason, Camerer et al. (1997) and others have postulated that workers may become less loss averse as they gain experience. In a recent study, Farber (2015) tests this theory on a large sample of New York City taxi drivers. Farber (2015) estimates a model of hours worked, similar to (6), separately for different experience groups and finds, as we do, that estimates of the coefficient on log hourly earnings increase with experience.

Following Köszegi and Rabin (2006) and others, Farber (2015) proposes that workers' income targets reflect expected incomes. Given an expected wage, a worker anticipates working a certain number of hours and earning a certain level of income. This income level becomes the worker's income target. Thus, only when realized wages deviate from expected wages do we expect to see reference-dependent behavior. In our study, labor supply elasticities are identified by variation in the lunar cycle, which is perfectly predictable. Even if fishermen form income targets based on expected wages and these income targets influence labor supply, our results cannot be driven by

this behavior. Furthermore, our estimates of the daily participation elasticity are much larger for retiring fishermen than for the full sample and for new entrants, and this decision can only be based on anticipated wages. It is also worth noting that Farber (2015) and Haggag, McManus and Paci (2017) find strong evidence of LBD in the New York City taxi industry. Thus, it is quite possible that the positive correlation between elasticity estimates and experience found in Farber (2015) is a result of the role of LBD in labor supply.

7 DISCUSSION

When wages increase with work experience, the marginal return to work does not simply equal the wage, and estimations of standard labor supply models that assume exogenous wage formation suffer from omitted variable bias and produce downward-biased estimates of the IES. However, as workers accumulate experience and approach retirement, returns to experience become a negligible component of the marginal return to work, and the standard model becomes a reasonable approximation of behavior. We test this prediction using data on the daily labor supply decisions of Florida lobster fishermen. We estimate an IES of 2.7 using a standard empirical model and a sample of highly-experienced fishermen, within months of retiring. Our estimate of the IES drops to 1.3 when we estimate a standard model on our full sample of fishermen, who have varying degrees of experience and are at different stages of the life cycle. Thus, estimating the IES using a sample unlikely to suffer from the bias induced by ignoring the role of LBD increases the estimate by more than a factor of 2. As an additional test of the LBD model, we estimate a standard model on a sample of fishermen participating in their first lobster season. Intuition and evidence suggest that the returns to experience are largest for these individuals. Therefore, the model predicts that the omitted variable problem in standard estimations will be particularly severe for this group. Consistent with the model, our estimate of the IES for these individuals is approximately zero.

Our results are important for several reasons. First, they suggest that the IES is much larger than suggested by much of the empirical micro-based literature. This lends empirical support to the use of relatively large labor supply elasticities in calibrated representative agent macroeconomic models. While proper care should be taken in applying our results in a macro environment, as macro elasticities depend on long-term labor force participation decisions and non-trivial aggregation across individuals at different stages of the life cycle, our estimates are consistent with larger aggregate

labor supply elasticities than would be predicted based on standard micro estimates of the IES.

Second, our novel estimation strategy and empirical results provide new and largely model-free evidence of the importance of LBD, which lends further credibility to predictions of these models. As demonstrated in Keane (2015) and Keane (2016), models with LBD generate starkly different predictions about behavior than the standard model of labor supply with exogenous wages. Although the IES remains a time- and individual-invariant parameter, the Frisch, Hicks, and Marshall elasticities become functions of the parameters of the wage process and individual preferences and, therefore, vary across individuals and over the life cycle.²⁶ Moreover, the well-known relationships among the elasticities implied by the standard model – that the IES and Frisch elasticity are equivalent, that the Frisch exceeds the Hicks, and that both exceed the Marshall – need not hold. One implication of this is that a consistent estimate of the Frisch elasticity no longer serves as an upper bound for the Hicks and Marshall and, therefore, cannot be used to calculate an upper bound on the welfare effects of tax changes.

Another consequence is that permanent tax changes can have larger short-run effects on labor supply than transitory tax changes. A transitory tax change affects only the current wage. With LBD, the smaller is the wage in proportion to the total marginal return to work, the smaller is the effect of transitory tax changes on total returns and, hence, the smaller is the labor supply response. Permanent tax changes, however, affect both current and future wages, which serves to decrease returns to experience and, therefore, decrease the total marginal return to work. An important policy implication, which Keane (2016) makes clear, is that this undermines the argument that transitory tax cuts are an ideal tool for short-term economic stimulus. LBD also implies that the effect of permanent tax changes in the long run can be much more profound because a reduction in current labor supply leads to lower future wages, amplifying the effect of a tax change on total lifetime labor supply.

²⁶Equation (5) makes clear that the Frisch elasticity is a function of wage and preference parameters. See equations (14a) and (19) in Keane (2016) for formulas of Hicks and Marshall elasticities under LBD.

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