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ABSTRACT

Labor Supply with Social Interactions: Econometric Estimates and Their Tax Policy Implications*

Our econometric research allows for a possible response of a person's hours worked to hours typically worked by members of a multidimensional labor market reference group that considers demographics and geographic location. Instrumental variables estimates of the canonical labor supply model expanded to permit social interactions pass a battery of specification checks and indicate positive and economically important spillovers for adult men. Ignoring or incorrectly considering social interactions in male labor supply can mis-estimate the response to tax reform by as much as 60 percent.

JEL Classification: J22, Z13

Keywords: labor supply, social interactions, reference group, instrumental variables, social multiplier, PSID

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1. Introduction

Social interactions, the situation where individuals respond to the actions of people with whom they interact, may have a biological basis or stem from information gathering. Social interactions are a potentially important aspect of economic behavior because interdependencies can affect how people react to the expected and unexpected changes in their environment, including ones caused by public policy. We investigate the econometric nuances and empirical importance of social interactions in labor supply with taxes where the interdependence is a response of the individual to the hours worked by the members of a reference group. We find evidence of a positive spillover effect in hours worked that is important for tax policy and demonstrate how ignoring or misinterpreting labor supply social interactions effects can lead to substantial under or overestimates of the labor supply effects of tax reforms.

The presence of social interactions in labor supply means that individuals respond to others' hours worked by a non-negligible amount. A social interactions effect is important because policy affecting the wages or another independent variable of a subgroup will not only affect the individual but also affect others in the individual's reference group. We therefore focus on the consequences of interdependence for the estimated effect of wages on labor supply, which economists use widely in welfare effect simulations of tax reform proposals. Our research contribution is to implement a tractable labor supply model with spillover effects and then demonstrate the value of econometric estimates of the importance of social interactions in labor supply for tax policy.

Theoretical solutions to optimal static or dynamic taxation in the presence of social interactions externalities use the parameters of the utility and attendant consumption and labor supply functions (Kooreman and Schoonbeek 2004, Abel 2005). To flesh out briefly the enriched policy implications of a labor supply model with social interactions consider a basic proportional tax reduction applied to married men in a case where one need be careful with potential social interactions effects. Suppose the proportional tax rate change applied only to families with disabled children. The subpopulation affected would be relatively small and scattered geographically; reference group effects could be ignored safely. Alternatively, suppose we were examining the effect of a proportional state income tax change on the highest earners in a state such as California, where many would live in the same area. Now feedback effects would be present. The labor supply elasticity to consider would then include non-negligible social interactions effects. Put simply, the benefits of empirical social interactions research are that after identifying any interdependencies the economist can perform a more complete welfare analysis.

Identification of social interactions is econometrically complex (Soetevent 2006, Lee 2007a,b). The primary challenge a researcher must confront is what is the correct reference group (Durlauf 2004). There is a wide-ranging belief that people in close proximity can have a significant effect on the individual's labor supply decisions (Weinberg et al. 2004). Similarly, there is labor supply research where reference points come from others who are demographically similar but need not live near each other (Woittiez and Kapteyn 1998). Here we synthesize the two possibilities whereby our econometric model allows the data to reveal reference groups that are multidimensional in demographic and geographic closeness with the weights left as free parameters to be estimated.

In summary, we address many of the practical issues related to identifying the effect of endogenous social interactions on an individual's actions. We create a flexible measure of the economic distance approximating the level at which individuals interact among one another. We define the economic distance between individuals as a combination of personal characteristics and physical distance. Our measure reflects the varying costs of interaction as higher economic distance implies higher cost of interaction, which implies a lower level of interaction. We then define the reference groups, each of which consists of persons who are in a close economic proximity, and compute hours worked for each person in the reference group (endogenous social interactions). We create and verify the econometric validity of an instrument from the mean of hours worked for persons who are in the adjacent reference group for the purpose of instrumenting endogenous social interactions. The specification lets us examine the core issue of whether the hours supplied by persons in close economic proximity are related.

To frame the importance of social interactions we purposely use cross-section data from 1976 so as to anchor our research to the seminal and oft cited cross-section studies of male labor supply by Hausman (1981) and MaCurdy et al. (1990). Our econometric results suggest positive and non-negligible social interactions in hours worked. Focal results are that U.S. male labor supply data (1) reject a model ignoring social interactions against one with spillovers and (2) reject a model with spillovers treated as exogenous against one with spillovers treated as endogenous. A regression model that ignores spillovers in labor supply underestimates the wage elasticity of labor supply by about 40 percent; if one uses a social interactions model but ignores endogenous interactions one underestimates the wage elasticity by over 60 percent. We conclude with a demonstration of how improperly accounting for social interactions can lead to substantial under or over estimation of the labor supply effects of tax reform.

2. Theory

Theories of social interactions have a long history in the economic literature. Theoretical exercises since Becker (1974) share the common feature that the utility of the individual is somehow affected by either utility or choices made by members of a reference group, who are people with whom the individual interacts. Especially interesting is the recent research into how information and species survival considerations may be the source of equilibrium social interactions in utility (Samuelson 2004; Rayo and Becker 2007a,b).

In our theoretical framework we follow Brock and Durlauf (2001, 2002) and Grodner and Kniesner (2006) who introduce interactions into a baseline model with additive total utility consisting of individual utility and social utility. We assume that the economy is in an equilibrium developed neighborhood structure (Durlauf 1996). In what follows we use the terms membership group, neighborhood, and community as equivalent and meaning persons who are part of the individual's reference group.

Consider now a general utility function that includes a negative spillover effect for others' hours worked:

$$\begin{gathered} V_{ig}\left(c_{ig}, h_{ig}; b_g\left(\mu_h\right)\right) = u_{ig}\left(c_{ig}, T - h_{ig}\right) - b_g\left(\mu_{hg}\right) s\left(h_{ig}\right) \\ \text{st.}\, c_{ig} \leq h_{ig} w_g, \end{gathered} \tag{1}$$

where $V_{ig}(\bullet)$ represents total utility of person i who belongs to the reference group g, $u(\bullet)$ represents a private utility over consumption (c) and leisure ($T - h$), where T is total available time, h is hours worked/labor supplied, and $\left[-b_g\left(\mu_h\right)s\left(h_{ig}\right)\right]$ is total social disutility of working. Unlike the canonical utility function, total disutility of hours worked depends on the level of $b_g\left(\bullet\right)$, which represents the importance of social disutility. For the individual *i* in reference group *g*, $b_g\left(\bullet\right)$ is increasing in average hours worked in the reference group, μ_{hg}, excluding the i^{th} worker (so $\mu_{hg}=\overline{h}_{(-i)g}$), with $b_g\left(0\right)=0$, $b_g\left(\infty\right)\rightarrow\infty$, and $b_g'>0$. Total social disutility also depends on $s\left(\bullet\right)$, which is the social disutility of individual hours worked (disutility of the individual from how others judge his or her work level) with $s\left(0\right)=s_0>0$, $s\left(\infty\right)\rightarrow 0$, $s'<0$, and $s''>0$; s_0 is autonomous social disutility, which is equal across individuals and reference groups. Finally, w_g is a wage rate in the reference group g.

Social disutility of individual's hours worked $s\left(\bullet\right)$ is always non-zero with a maximum value of s_0 at zero hours worked.[1] Social disutility of one's hours worked seems most likely to be decreasing $\left(s'<0\right)$ at a decreasing rate $\left(s''>0\right)$. The decrease in the social disutility means that as individuals work more hours they believe others judge them less harshly. A decrease of social disutility at a decreasing rate means that as individuals work more hours the gain of appearing better in the eyes of peers is getting smaller. The worker may also view certain levels of hours worked as satisfactory and care less and less about opinions of others as long as the worker reaches some accepted levels of hours worked according to his or her personal belief system.[2]

A typical maintained hypothesis is that the importance of the social utility term, b_g, is increasing in the average hours worked in the individual's reference group $(b_g'<0)$.

So, when workers see an environment filled with other hard-working people they expect to be judged more if they stick out more relative to the labor market performance of others. The individual may feel more negatively perceived if further down the ranking of work effort.

After setting up the Lagrangian, taking the total differential of the first-order conditions of (1), and performing comparative statics based on the properties of social interactions in labor supply just described, the result emerging is that

$$\frac{dh}{d\mu_h} = \frac{-\overbrace{b'}^{(+)}\overbrace{s'}^{(-)}}{\underbrace{bs''(h)}_{(+)} + \underbrace{2wu_{ch} - u_{hh} - w^2 u_{cc}}_{(+)}} > 0 \qquad (2)$$

with the partial derivatives of private utility, $u_{cc} < 0$ and $u_{hh} < 0$.

In equation (2) an increase in average hours worked in the reference group increases the individual's hours worked. The intuition is that when the average labor supply increases the parameter b increases, social disutility increases, and total utility decreases. To find a new maximum total utility the worker increases hours worked; although utility decreases because hours worked are a bad ($u_h < 0$), an increase in the labor supply reduces social disutility because $s' < 0$. Overall, an increase in hours worked increases total utility because the decrease in social disutility is higher than the decrease in individual utility. The model suggests that workers who are in an environment with relatively many hard working people are induced to work more hours than when there is no social interactions effect.

The utility function $u_{ig}(c_{ig}, h_{ig}; \mu_{hg}) = [(h_{ig} - b)/\beta]\exp-[1+\beta(c_{ig} + \tilde{s})/(b - h_{ig})]$, where $b = \alpha/\beta$, $\tilde{s} = (s/\beta - (\alpha/\beta^2)$, α and β are parameters, and s is a linear combination of reference group variables (μ_{hg}), is the utility function derived by Hausman (1980, 1981) amended to include social interactions. We will use the resulting linear labor supply function in order to anchor our results to Hausman's and MaCurdy's influential research, which facilitates judging the economic importance of adding social interactions to labor supply. In the empirical work to follow we regress individuals' hours worked on average hours worked in their reference groups, ceteris paribus. A positive coefficient on labor supplied by the reference group indicates the presence of a positive spillover effect in hours worked (Woittiez and Kapteyn 1998, Aronsson et al 1999). We now flesh out the econometric details involved with examining possible exogenous and endogenous social interactions in individual labor supply.

3. Econometric Model

The canonical linear labor supply model with social interactions added that we estimate is

$$h = \theta + \alpha\omega + \beta\upsilon + \gamma x + \delta_1 \overline{h}_{(-i)g} + \delta_2 \overline{x}_{(-i)g} + \varepsilon \ , \qquad (3)$$

where ω is the after-tax real wage, υ is after-tax virtual income, x is a vector of individual control covariates, $\overline{h}_{(-i)g}$ is reference group average labor supplied, $\overline{x}_{(-i)g}$ is the vector of control covariate averages for the reference group, ε is the error term, and [θ, α, β, γ, ρ, δ_1, δ_2] are parameters to estimate.

3.1 Independent Variables

The net wage rate (ω) uses a marginal tax rate τ provided by the PSID, and is $\omega = (1-\tau)w$. Virtual income (υ) also uses the marginal tax rate from the PSID.[3] To control for possible endogeneity when estimating (3) we instrument both the after tax wage and virtual income using last year's gross wage and non-labor income (Ziliak and Kniesner 1999).

The control covariates in labor supply include number of children less than six years old, family size, an indicator if the person is more than 45 years old, the equity the family has in their house, and an indicator of a physical or nervous condition that limits the amount of work, which are standard exogenous explanatory variables in labor supply studies. Finally, in some specifications x includes hours worked in the previous year (h_{-1}) to allow for the possibility noted by Rayo and Becker (2007a,b) that the reference point in utility may depend not only on reference group outcomes but also on the individual's habits.

3.2 Social Interactions Variables

The mean for hours worked in the reference group is the sample average of hours worked for other people who are close in economic distance to the worker. In the computing the average we exclude the individual for whom we are computing a reference group mean outcome. The estimated value of the parameter δ_1 represents the effect of endogenous social interactions in hours worked.

Computing the mean of covariates takes multiple steps. First, we create a proxy variable summarizing the information in the exogenous covariates. We then use factor analysis and take the first factor as a proxy variable for exogenous information. The new variable does not have a direct interpretation because it is standardized to have zero mean and unit variance, however it is highly correlated with all the exogenous variables as well as the individual's hours worked. The mean in the reference group for the created proxy variable uses the same range of the economic distance variables as used for computing mean hours worked, again excluding the person for whom we are computing the reference group mean. The proxy variable controls for the common characteristics of the reference group, and the estimated coefficient δ_2 indicates any presence of exogenous social interactions.

3.3 Identifying Social Interactions

The form of the labor supply equation in (3) can identify the presence of both endogenous (in the dependent variable) and exogenous (in the independent variables) social interactions. Identification requires some additional structure, though (Manski 1993, Moffitt 2001).

If the reference groups are completely separable then a randomly distributed shock that affects hours worked for some individuals and not others can help identify endogenous social interactions (Moffitt 2001). When reference groups overlap there are a variety of empirical approaches including repeated samples (Aronsson et al. 1999), structural models (Brock and Durlauf 2002, Kapteyn et al. 1997, Krauth 2006), aggregated data (Glaeser et al. 2002), within versus between variation (Graham and Hahn 2005), or spatial econometric techniques (Kelejian and Prucha 1998, Lee 2007a,b).

Alternatively, suppose there are workers who belong to more than one reference group, and we use them to compute the (endogenous) mean for reference group hours worked. Hours worked by people in the adjacent reference group can now be an instrument; this is similar to using past values of the dependent variable in a dynamic panel data model (Arellano and Bond 1991). Here we use as an instrument the mean for workers in the adjacent reference groups, which are defined by a social grid with two social coordinates from factor analysis. The instrument is correlated with mean hours worked in the individual's reference group (endogenous social interactions) because people in the specific reference group and the adjacent reference group belong to the same economic neighborhood. The instrument should also be uncorrelated with unobservables affecting individual labor supply because the particular individual does not belong to the adjacent reference group.[4] In any event, the IV approach that we use will be checked in the usual ways for weak instruments and that the overidentifying restrictions are satisfied and if the checks are passed then we are no less comfortable with our approach just like any other IV application.

Figure 1 illustrates our particular identification strategy. We present the hypothetical two-dimensional social coordinate space with two reference groups: g_1 and g_2. Suppose now that individual $h^0_{g_1}$ belongs to the reference group g_1 and responds to the outcomes of the members of the reference group, represented by the observations labeled as $h^1_{g_1}$ and $h^2_{g_1 g_2}$ (empty and gray-filled circles). If we use the mean of all $h^1_{g_1}$ and $h^2_{g_1 g_2}$ observations (referred further as $\overline{h}^{(-0)}_{g_1}$) as an independent variable in the regression (3) to try to identify endogenous social interaction in $h^0_{g_1}$ the coefficient will be biased because observations $h^1_{g_1}$ and $h^2_{g_1 g_2}$ are also affected by the outcome $h^0_{g_1}$, which causes endogeneity in the $\overline{h}^{(-0)}_{g_1}$. However, if there are observations in the reference group g_1 that also belong to the neighboring reference group g_2, then part of $\overline{h}^{(-0)}_{g_1}$ attributed to the outcomes $h^2_{g_1 g_2}$ can be instrumented by the outcomes of the members of the reference group g_2, denoted by $h^3_{g_2}$. If the usual diagnostic checks are passed plus an additional one developed in Lee (2007b) that reference group size varies then we can reasonably use instrumental variables (IV) estimation because $h^3_{g_2}$ are correlated with all $h^2_{g_1 g_2}$ observations because they belong to the same reference group, and $h^3_{g_2}$ are not correlated with the error terms associated with either $h^0_{g_1}$ or $h^1_{g_1}$ observations because they do not belong to the same reference group. Observations $h^3_{g_2}$ are transitorily correlated with the outcomes $h^0_{g_1}$ and $h^1_{g_1}$ only through the deterministic part of observations $h^2_{g_1 g_2}$.

In practice, if we instrument observations $h^2_{g_1 g_2}$ with outcomes $h^3_{g_2}$ there may still be observations $h^1_{g_1}$ that are not instrumented and thus will make a part of the $\overline{h}^{(-0)}_{g_1}$ endogenous, which is the case presented in Figure 1. Instead of using just one reference group we can imagine using a full set of observations in the adjacent reference groups that form the ring around the particular reference group (represented by the dotted circle).

4. Data

We use data from the University of Michigan's Panel Study of Income Dynamics (PSID) collected in years 1975 and 1976 (PSID Wave IX). One reason for using the PSID is that it is the most frequently used data to study U.S. labor supply (Blundell and MaCurdy 1999, Ziliak and Kniesner 1999). We purposely choose the 1976 cross-section of the PSID data because we seek to understand the possible importance of social interactions in labor supply by anchoring our estimates to the influential research of Hausman (1980, 1981) and MaCurdy et al. (1990) who use the same data to examine how taxes affect labor supply without modeling social interactions.

4.1 Sample

We follow the sample selection process described in Eklöf and Sacklén (2000) who compare the studies by Hausman (1981) and MaCurdy et al. (1990) to which we anchor our research. Both studies estimate an almost identical linear labor supply model with income taxation. We select observations according to the following criteria: married males 26–55 years old with positive hours worked in 1974 and 1975 (but no higher than 5096 annual hours), who are heads of households in the cross-sectional random sub-sample; there were no changes in the family composition of the head or wife (others can change) in years 1974–1975; the head is not retired, permanently disabled, housewife, student, or other; the household resides in the United States; and the head is not self-employed or a farmer. Using our exclusion criteria for the 1976 PSID we obtain 1077 observations, which is close to the Hausman sample of 1084 and the MaCurdy sample of 1018 as reported by Eklöf and Sacklén (2000).[5]

4.2 Individual Regression Variables

The wage rate comes from a direct question in the PSID, including an imputed value for workers who are not paid by the hour. We also estimate a wage equation to impute hourly wages for observations with unobserved or truncated wages. In particular, we use observations that have positive and not top-coded wage rates (839 observations) to estimate a Tobit regression that uses as the dependent variable observed (un)truncated wages on a constant term, age, age squared, years of schooling, years of schooling squared, college degree, and family size. We then use the estimated wage equation to produce a fitted value for all wages. The procedure is similar to that in Hausman (1981), and so our mean hourly wage is \$6.17, which nearly identical to the \$6.18 reported by Hausman.

Hours worked, the dependent variable, also comes from a directly asked question in the PSID. Non-labor income is a constructed variable that is the difference between total 1975 taxable income of the husband and wife and total 1975 labor earnings of the husband. The hours worked and the non-labor income measures we use are also those of MaCurdy et al. (1990). Other independent variables include number of children less than six years old (KIDSU6), family size (FAMSIZ), an indicator variable for individuals more than 45 years old (AGE45), the amount of equity the family had in its house (HOUSEQ), and an indicator of a physical or nervous condition that limited the amount of work the respondent could do (BHLTH). Appendix A presents descriptive statistics for all regression variables.

4.3 Reference Group and Economic Distance

Specifying the composition of the individual's reference group is the researcher's central decision in any study of interdependence (Manski 1993, 2000). Implementing the reference group concept means acknowledging that people who are in relative economic proximity to each other may interact with one another because the cost of interactions is low. We use the concept of economic distance among individuals as an indicator of the potential significance and magnitude of workers' interdependencies (Conley 1999). We take people who are in close economic distance as belonging to the same reference group.

Economic distance is a combination of whether the workers are similar demographically and live in close physical proximity. We use a combination of personal and family characteristics to define demographically similar persons and use the distance between centers of counties in which people reside for their relative geographic locations.

There are multiple difficulties involved with selecting from a large variety of characteristics to measure economic distance. Acknowledging that each characteristic measure has a difference scale, and determining the relative importance of each input variable on economic distance, we use a statistical model of factor analysis (Woittiez and Kapteyn 1998). The factor analytic model deals naturally with characteristics having different measurement scales; the procedure standardizes individual variables then fits a linear model to find common latent variables called factors (Bai and Ng 2002, Bai 2003). The intuition is that there are unobservable variables (factors) that are orthogonal to one another and that are strongly correlated with observed variables. We use the factors as social coordinates to establish reference groups.

Because the typical variables explaining labor supply can affect whether workers interact with each other by being related to economic distance, our factor analysis inputs all independent variables from the econometric labor supply model (3). We also use physical coordinates indicating the location by the center of the county where the person resides. We use two factors to summarize demographic and physical coordinates because there is usually a much better fit with multiple factors than with only one factor, but using too many factors tends to be uninformative.[6] By using two factors we have the convenient feature that the computed latent variables serve as two social coordinates (SocCoord1, SocCoord2) for where individuals are located on a social interactions grid with economic distance measured by Euclidean distance between two points.

5. Econometric Results: Labor Supply with Social Interactions

Because in our study there is no clearly defined reference group we first select persons likely to have interdependent labor supplies by using the two social coordinates to define overlapping neighborhoods. The reference group now defined, we then estimate the labor supply model in (3) using instrumental variables for identification. If the appropriate econometric specification checks are satisfied, we then interpret the social interactions effects in terms of endogenous versus exogenous wage effects.

5.1 Selecting the Reference Group

Because we do not have direct information on who belongs to the reference group for a particular person we use a statistical procedure to infer it from the location and characteristics of the group's members. We believe that our observations are representative for working married men in terms of their individual characteristics and spatial distribution.

We can think of the reference group as a ring of certain radius centered around the individual in two-dimensional social coordinate space (Figure 1). The problem is then to select the radius best representing the borders of the reference group. The borders selection problem is key because we use sample observations to compute the characteristics of close-by individuals. Each observation establishes possible multiple reference groups so that careful selection of borders is critical here for identification.

To find borders for the membership groups we use a result from spatial econometrics that as the reference group size expands the coefficient on endogenous social interactions tends to minus infinity (Kelejian and Prucha 2002).[7] In our application endogenous social interactions are represented by the mean of hours worked by others in the worker's reference group, AnnHSRG_0_*R*, where *R* indicates the radius dimension of the reference group's circle. If there are social interactions present at a certain size of the reference group, then the upward bias because of reference group labor supply endogeneity will overcome the statistical tendency for $\hat{\delta}_1$ in (3) to become negative as the neighborhood size increases, (Anselin 2001). The reference group with the most positive

$\hat{\delta}_1$ in exploratory estimates of (3) then reveals the size of the worker's reference group.

In Table 1 we present results from baseline labor supply regressions with a social interactions variable, AnnHSRG_0_*R*. Estimation starts with R = 1, which means that the average of hours worked uses nearby workers in the social space within the distance of 0.1 or less. When the indicator R = 1 the reference group has around 13 workers. As the size of the reference group increases in the social space (the radius indicator R increases), the number of persons who are considered to be economically close to a worker increases from 44 to about 271 in Table 1.

As expected a priori, the coefficient on average hours worked by neighboring persons is increasingly negative across the columns of Table 1, going from about –0.2 to –1.5 as the reference group size increases. Such a tendency will be observed for any estimator including the IV regressions of Table 1 (Kelejian and Prucha, 2002). Critical to our research is that the reference group labor supply coefficient becomes positive at the size of the reference group where radius indicator R = 2.

The importance of Table 1 is that the pattern of regressions reveals the group size with the largest upward bias due to endogeneity of the AnnHSRG variable. The endogeneity caused by labor supply interdependencies is most positive for the range (0,0.2), so we pick 0.2 as the radius most closely capturing the true size of the reference group. Results from a Moran I test (Anselin 2001, p. 323) confirm the presence of social interactions in hours worked and that the radius we adopt to define the reference group based on the preliminary regression in Table 1 also maximizes the Moran I statistic measure of association. The practical consequence of our specification search is it indicates that the average reference group contains about 44 persons ($\bar{n}_g = 44$), which means that it is small enough to guarantee sufficient outcome variation across groups but large enough so that the computed average hours worked are meaningful and have relatively small error due to aggregation. Our results also satisfy the identification condition for general spatial econometric models established in Lee (2007b) that groups vary in size ($\sigma_{n_g} = 38, n_g$(max) = 139).

5.2 Social interactions Effects

The focus of our research is on examining interdependence in hours worked using the canonical model of labor supply applied to cross-section data. This anchors our results for purposes of interpretation to the influential labor supply research of Hausman (1980, 1981) and MaCurdy et al. (1990).

We first confirm that our estimates for the uncompensated wage and income elasticities are similar to the results of Hausman and MaCurdy et al. The first column of Table 2 presents IV regression wage and income coefficients for their canonical models of labor supply. The uncompensated wage elasticity at the means is 0.14 and the income elasticity at the means is –.008; both values are typical estimates in the standard econometric labor supply literature that serves as our starting point for judging the importance of social interactions.

Our focal regression results are presented in the second column of Table 2, where we include both habits and social interactions. We also use as a regressor the average of the proxy variable for the exogenous variables constructed via factor analysis (IndVORG_2_6). The estimated social interactions effect is that a 10 hours increase in the reference group labor supplied would increase individual's hours worked by about 6 hours. Comparing columns two and three of Table 2 yields the important result that the estimated social interaction effect is significant statistically and economically reasonable in magnitude only when habits in labor supply are part of the specification.[8]

It is important to re-emphasize that the estimated social interactions effect, $\hat{\delta}_1$, which is the impact of average hours worked by persons in the worker's reference group (AnnHSRG_0_2), has the expected sign and magnitude only after the interdependence has been instrumented, which we do in Table 2. The results in Table 1 are inconsistent because they suggest the presence of endogenous social interactions (Durbin-Wu-Hausman test rejects exogeneity at the 5 percent level). Because of the difference between the results in Tables 1 and 2 we need to emphasize the method we use to construct the instrument for social interactions in labor supply.

As noted, there are no obvious variables to provide exogenous variation with which to instrument reference group work effort, so we use the structure of the data to construct an instrument for the reference group's labor supplied. Taking reference groups as overlapping with boundaries as fixed, average hours worked by persons in the adjacent reference groups can be instruments. The outer boundary of the persons for the instrument group will be exactly twice the size of the radius for each neighborhood because there may be workers who are located exactly on the boundary for both the reference group of interest and the adjacent reference group.[9] We construct hours worked by individuals in the outside ring in Figure 1, (0.2, 0.6], which has an average of 226 observations for each instrument group. First-stage goodness of fit and Sargan test results for the regressions in Table 2 confirm that our instruments (for all three right-hand side endogenous regressors) are valid in terms of passing the standard checks for weak instruments and that the overidentifying restrictions are satisfied. Equivalently, the strength of our identifying instruments here means that the potential bias of the IV estimator of the social interactions effect in Table 2 is relatively tiny: less than 4% of the potential bias of OLS (Hahn and Hausman 2003; Stock and Yogo 2005).

5.3 Additional Econometric Validity Checks of the Reference Group

In is instructive to examine how our results may or may not be robust to the sizes of the reference group or adjacent groups comprising the instrument set. How might our results change by (1) shrinking the outer circle boundary in Figure 1, which leaves the reference group size the same but decreases the number of observations viewed as nearest neighbors for the reference group, or change by (2) shrinking the inner reference group circle boundary in Figure 1, which makes the reference group smaller?

In the first sensitivity experiment, as the instrument group shrinks the IV estimated social interactions effect is similar while becoming statistically less precisely estimated. Our interpretation is that the instrument loses power as the size of the instrument set shrinks.

In the second sensitivity experiment, we find that when the reference group size shrinks the estimated social interactions effect is again basically unchanged although statistical efficiency of the estimate again decreases. We interpret the result of the second sensitivity experiment as indicating that the range for the reference group is well chosen because within the group there should be a similar level of interactions, and we are just choosing a progressively smaller and small subgroup who still interact.

Having discussed the sensitivity of our results instrument construction we now turn our attention to the economic interpretation and policy implications of our estimated social interactions effects in male labor supply.

5.4 Interpreting the Importance of the Estimated Social Interactions Effect

The presence of social interactions in labor supply means that individuals respond to others' hours worked by a non-negligible amount. A social interactions effect is important because policy affecting the wages or another independent variable of a subgroup will not only affect the individual but also affect others in the reference group. We therefore focus on the direct versus the indirect effect of interdependence. In particular, we study the consequences of interdependence for the estimated effect of wages on labor supply, which economists use widely in welfare effect simulations of tax reform proposals.

Taking the mean values in equation (3) and focusing on hours worked and wages,

$$\overline{h} = \alpha\overline{\omega} + \delta_1\overline{h} \Rightarrow \overline{h} = \alpha\frac{1}{1-\delta_1}\overline{\omega}\,, \tag{4}$$

where the quantity $1/(1-\delta_1)$ is known as the global social multiplier because it represents the effect of social interactions at the highest level of aggregation (Glaeser et al. 2003). The total effect of a wage change can be decomposed into

$$\partial\overline{h}/\partial\overline{\omega} = \frac{\alpha}{1-\delta_1} = \alpha + \frac{\alpha\delta_1}{1-\delta_1}\,, \tag{5}$$

where α is the exogenous effect, and $(\alpha\delta_1)/(1-\delta_1)$ is the endogenous effect. Notice that the endogenous effect depends on both the magnitude of the initial exogenous change and the social multiplier.

Multiplying equation (5) by $\overline{\omega}/\overline{h}$ the uncompensated elasticity is

$$\eta_{hw,total} = \eta_{hw,exogenous} + \eta_{hw,endogenous}\,, \tag{6}$$

where $\eta_{hw,exogenous} = \alpha\overline{\omega}/\overline{h}$ and $\eta_{hw,endogenous} = \alpha\delta_1\overline{\omega}/(1-\delta_1)\overline{h}$. For $\delta_1 < 0.5$ the exogenous effect is larger than the endogenous effect, but for $\delta_1 > 0.5$ the endogenous effect is larger. As we will later emphasize, the decomposition in (6) underscores how ignoring labor supply interdependencies may have serious consequences for the elasticity estimates of interest.

Using the values from the second column of Table 2, the total uncompensated wage elasticity of labor supply at the means is 0.22, with an exogenous part of 0.08, and a endogenous part of 0.14. In comparison, the baseline model results from column one of Table 2 are an uncompensated net wage elasticity of 0.13. When we purposely ignore social interactions the estimated exogenous wage effect is about 60 percent too high; the positive bias in the canonical model happens because the single (wage) coefficient estimate also imbeds the effect of labor supply interdependencies. The twin findings that (1) the wage elasticity has two unequal and sizeable parts in the social interactions model and that (2) the wage coefficient of the traditional model has sizeable omitted variable bias have important consequences for evaluating tax policy.

5.5 Implications for Tax Policy Calculations

We have noted that numerical solutions to optimal income taxation need appropriate econometric estimates. Further our core results are that for U.S. male labor supply a regression model that ignores spillovers in labor supply underestimates the wage elasticity of labor supply by about 40 percent; if one uses a social interactions model but ignores endogenous interactions one underestimates the wage elasticity by over 60 percent.

It is less obvious how we should apply estimates that let the policy-maker apportion the total wage elasticity into segments with and without social interactions.

Some back-of-the-envelope calculations for the proportional tax rate case are instructive. The preferred model in Table 2, column 2 implies that a 10 percent comprehensive tax rate cut would raise male labor supply by as much as 2.2 percent when social interactions are considered; ignoring social interactions would lead to about a 60 percent under-estimate of the labor supply effect of the tax cut (0.8 percent). Less well established is how to use in policy calculations our decomposition of the total wage elasticity into its exogenous component (+0.08) and its endogenous social interactions component (+0.14).

To emphasize the enriched implications of a labor supply model with social interactions let us again note a case where one need be careful with potential social interactions effects. Suppose there is a proportional tax rate change applied only to families with disabled children. The subpopulation affected would be relatively small and scattered geographically; the reference group effects could be ignored safely, and the appropriate elasticity to use would be closer to 0.08 than to 0.22. Alternatively, suppose we were discussing the effect of a proportional state income tax change on the highest earners in a state such as California, where many would live in the same area. Now feedback effects would be present. The elasticity to use would then include non-negligible social interactions effects and would probably be closer to 0.22 than to 0.08.

The importance of gauging what is the correct elasticity in terms of the exogenous and endogenous parts is only useful if we can define whether or not a particular group will be affected by interactions. If the persons who are affected do not belong to the same reference group then most likely we would only observe the exogenous effect, and the elasticity would overestimated if we used an elasticity that contained both exogenous and endogenous components, which was the first example in the previous paragraph. If the tax reform applied to members of a reference group, though, then there would be a full-blown feedback effect and the elasticity that used only an exogenous component would underestimate the total labor supply effect, which was the second example above.

6. Conclusion

Our research uses the canonical (linear in means) model of labor supply that adds possible social interactions in hours worked. We flesh out the econometric nuances of testing whether an increase in hours worked by the members of the reference group increases hours worked for the individual (endogenous social effect). The reference group here contains persons in close economic distance to each other. Our measure of economic distance uses factor analysis, which allows mapping neighborhood variables into a two-dimensional social space. Our identification strategy builds on the likelihood that some persons belong to more than one reference group so that their hours worked may be used to instrument for endogenous labor supply of individuals in the worker's reference group. As in any other IV exercise we are careful to apply checks of instrument strength and that the overidentifying restrictions are satisfied.

In our regression model of married men's labor supply if social interactions are treated as exogenous there is no estimated effect of the reference group behavior on the individual worker's behavior. When we instrument mean hours worked of the reference group and include individual habits in labor supplied we find a social interactions effect that is reasonable both statistically and economically. The estimated total wage elasticity of labor is 0.22, where about one-third is due to the exogenous wage change and two-thirds is due to social interactions effects.

The policy implications are that if one is to understand fully the labor supply and welfare effects of income taxes, which may be conditioned on demographic and location information, a model including social interactions is best. Equally important is a proper interpretation of the social interactions model results. We demonstrate how a mis-specified model or a properly specified model that is mis-interpreted can easily lead to mis-estimates of the labor supply effects of tax reform by as much as 60 percent.

Endnotes

1. The baseline level of social disutility, s_0, is exogenous, and we begin by assuming that it is constant for all individuals across all groups. Homogeneity is important because if s_0 varies either across individuals due to heterogeneity or across the groups due to reference-group specific characteristics, then it is impossible to discuss the effect of social utility $b(\bullet)$ versus the effect of autonomous social utility s_0.
2. The overall result here would not change if $s'' < 0$.
3. υ = [NLI + (τ – (TT/(TI – NLI)) × (TI – NLI))], where NLI is non-labor income, TT are total taxes, and TI is taxable income (Ziliak and Kniesner 1999).
4. A strategy similar to ours just described is in Case and Katz (1992), who instrument for the endogenous effect using the average levels of adjacent neighbors' characteristics that are supposedly exogenous. Similarly, Evans et al. (1992) instrument school composition with city-wide variables for the unemployment rate.
5. The difference between the number of observations used by MaCurdy et al. (1990) and our study comes from the fact that we dropped two observations because the head's age was missing and that we did not exclude persons who were self-employed and farmers in 1975 but not in 1976 (changed employment status). Due to restricting the sample to individuals who also reported hours worked for year 1974, we have a final sample of 910 men.
6. The first factor loads primarily on demographics and explains about 75 percent of

the total variation in the variables. The second (rotated) factor loads primarily on location and then explains about 15 percent of the information.

7. The intuition behind the result is that as the size of the group used to produce the average grows it approaches a similar value for everyone and become increasingly collinear with the regression constant term.

8. The coefficient on the hours worked for the reference group needs to be less than 1.0 here. Otherwise, a one hour increase in the mean hours worked for the reference group would induce a worker to increase his labor supply by more than one hour, which in turn would increase the hours worked for other men in the individual's reference group even further. The labor market equilibrium would be explosive, and a small positive shock to hours worked for any individual in the reference group would cause a domino effect where in the limit all workers choose the maximum feasible hours.

9. The result stems from symmetric boundaries around each member. We thank Dan Black for that observation.

Table 1. Selection of the Reference Group Using IV Regression

	(1) AnnualHours	(2) AnnualHours	(3) AnnualHours	(4) AnnualHours	(5) AnnualHours	(6) AnnualHours
AfterTaxWage	**52.5361**	**68.4734***	**71.6107****	**71.8010****	**68.8683***	**68.9533***
	(36.3663)	(35.9633)	(35.4610)	(35.8352)	(35.6676)	(35.4563)
VirtualInc	−**0.0034**	−**0.0031**	−**0.0040**	−**0.0047**	−**0.0051**	−**0.0055**
	(0.0059)	(0.0058)	(0.0058)	(0.0057)	(0.0057)	(0.0057)
AnnHSRG_0_1	−0.1978**					
	(0.0867)					
AnnHSRG_0_2		0.0626				
		(0.1432)				
AnnHSRG_0_3			−0.2042			
			(0.2411)			
AnnHSRG_0_4				−0.4982		
				(0.3231)		
AnnHSRG_0_5					−0.9685***	
					(0.3566)	
AnnHSRG_0_6						−1.5021***
						(0.4709)
Observations	879	910	918	922	922	922
Average obs in ref group	13.33	44.53	89.19	142.56	204.13	271.21
Identifying Instruments	WageRate75, NLIncome75	WageRate75, NLIncome75	WageRate75, NLIncome75	WageRate75, NLIncome75	WageRate75, NLIncome75	WageRate75, NLIncome75

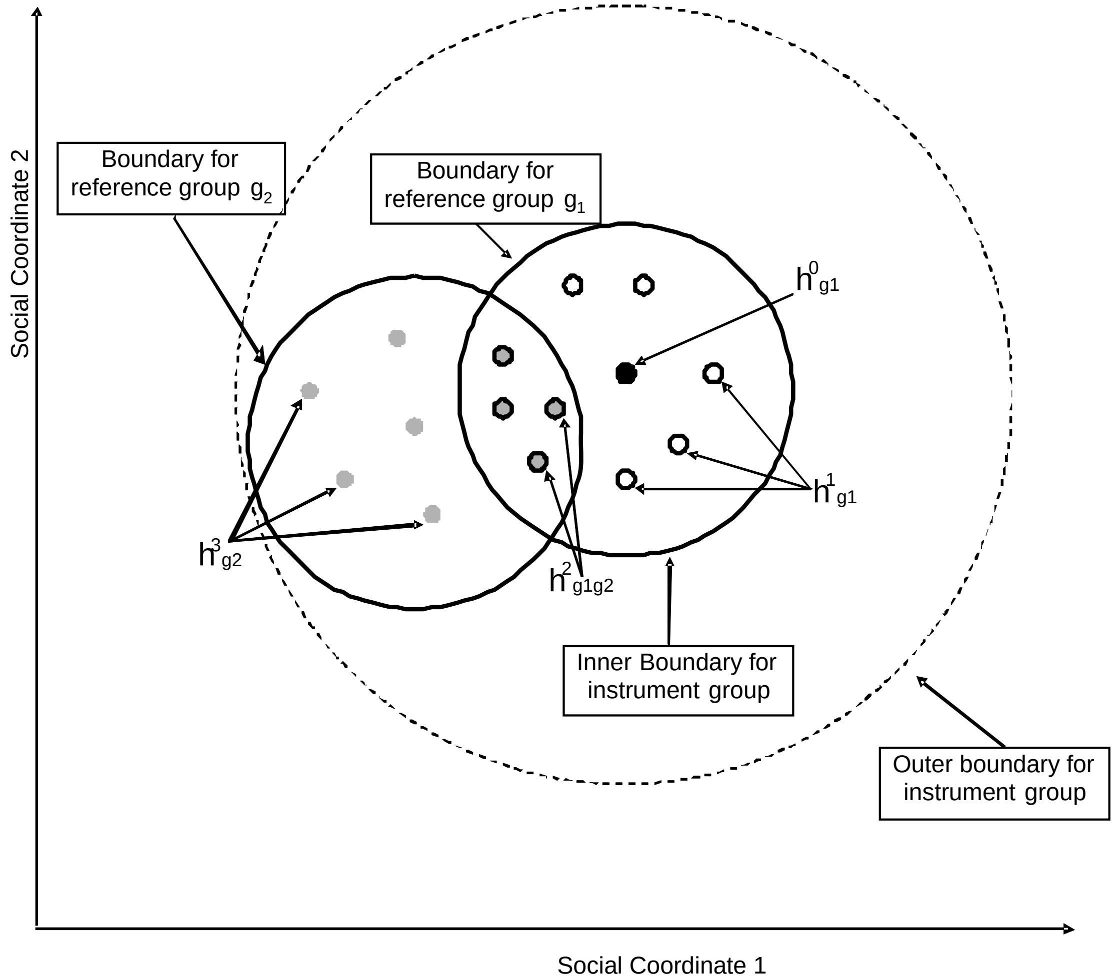
Standard errors in parentheses
Endogenous variables' coefficients in bold. Weak instrument check statistics appear in Table 2.
Additional Control Variables: KIDSU6, FAMSIZ, AGE45, HOUSEQ, BHLTH, Constant
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2. IV Regressions with Social Interactions

Dependent Var: Annual Hours Worked	**(1) Baseline**	**(2) Social interactions and habits**	**(3) Only habits**	**(4) Only social interactions**
AfterTaxWage	**66.6982***	**38.5373**	**30.5734**	**81.6429****
	(35.5604)	(28.6798)	(28.1246)	(37.3766)
VirtualInc	−**0.0031**	**0.0000**	**0.0011**	−**0.0055**
	(0.0058)	(0.0047)	(0.0045)	(0.0061)
IndVRG_0_2	−318.8201	−317.4740	−284.0008	−385.0609
	(381.9788)	(307.9343)	(302.0874)	(401.1535)
AnnHSRG_0_2		**0.6379****		**1.3128*****
		(0.2689)		(0.3532)
Observations	910	910	910	910
Sargan test		0.212		0.081
P-value		0.645		0.776
Identifying Instruments	WageRate75 NLIncome75	WageRate75 NLIncome75 AnnHSORG_2_6 IndVORG_2_6	WageRate75 NLIncome75	WageRate75 NLIncome75 AnnHSORG_2_6 IndVORG_2_6

Standard errors in parentheses
Endogenous variables' coefficients in bold. F(Shea partial R^2) = 53.0(0.189), 368.1(0.621), 51.9(0.188)
Additional control variables in all equation: KIDSU6, FAMSIZ, AGE45, HOUSEQ, BHLTH, Constant
Additional control variable in (2) and (3): AnnualHours75
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1. Demonstration of the Identification Strategy for the Endogenous Social Interactions.



Appendix A. Descriptive Statistics

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
AnnualHours	910	2236.864000	536.701100	288.000000	4917.000000
AnnualHour75	910	2247.385000	540.086500	320.000000	4500.000000
AfterTaxWage	910	4.692693	1.198573	0.542700	7.488000
WageRate	910	6.272303	1.794132	0.670000	9.900000
WageRate75	910	5.479915	0.636453	3.655642	6.837162
VirtualInc	910	5138.557000	4364.210000	−965.000000	45593.000000
NLIncome	910	3710.268000	4700.172000	−7900.000000	57640.000000
NLIncome75	910	3298.155000	3984.506000	−10000.000000	26000.000000
AnnHSRG_0_2	910	2210.108000	134.322300	1180.000000	2950.667000
AnnHSORG_2_6	910	2214.600000	53.725650	2009.458000	2477.579000
IndVORG_2_6	910	301892.000000	5444115.000000	−1.534880	1.369547
IndVRG_0_2	910	352303.000000	0.035230	−1.760330	1.598270
KIDSU6	910	0.445055	0.696331	0.000000	3.000000
FAMSIZ	910	3.873626	3.873626	2.000000	9.000000
AGE45	910	1.748352	3.108485	0.000000	11.000000
HOUSEQ	910	18511.900000	16930.990000	−5000.000000	120000.000000
BHLTH	910	.051648	.221438	0.000000	1.000000

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