

IZA DP No. 5934

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August 2011

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August 2011

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ABSTRACT

Social Interactions in the Labor Market^{*}

We examine theoretically and empirically social interactions in labor markets and how policy prescriptions can change dramatically when there are social interactions present. Spillover effects increase labor supply and conformity effects make labor supply perfectly inelastic at a reference group average. The demand for a good may also be influenced by either a spillover effect or a conformity effect. Positive spillover increases the demand for the good with interactions, and a conformity effect makes the demand curve pivot to become less price sensitive. Similar social interactions effects appear in the associated derived demands for labor. Individual and community factors may influence the average length of poverty spells. We measure local economic conditions by the county unemployment rate and neighborhood spillover effects by the racial makeup and poverty rate of the county. We find that moving an individual from one standard deviation above the mean poverty rate to one standard deviation below the mean poverty rate (from the inner city to the suburbs) lowers the average poverty spell by 20–25 percent. We further consider overall labor market outcomes by examining theoretically the socially optimal wealth distribution. Interdependence in utility can mitigate the need to transfer wealth to low-wage individuals and may require them to be poorer by all objective measures. Finally, we quantify how labor market policy changes when there are household social interactions. Labor supply estimates indicate positive economically important spillovers for adult U.S. men. Ignoring or incorrectly considering social interactions can mis-estimate the labor supply response of tax reform in the United States by as much as 60 percent.

NON-TECHNICAL SUMMARY

We explain how policy prescriptions can change dramatically when there are social interactions present. Spillover effects increase labor supply and conformity effects make labor supply constant at a reference group average. The demand for a good or the labor input may also be similarly influenced by such social interactions. Individual and community factors may influence poverty spells, which we quantify. Finally, we consider overall labor market outcomes including the socially optimal wealth distribution more efficient income tax structures. Ignoring or incorrectly considering social interactions can mis-estimate the labor supply response to U.S. tax reforms by as much as 60 percent.

JEL Classification: D11, J22, Z13 D31, D63

Keywords: social interactions, spillover, conformity, inequality, poverty, labor supply, reference group, social multiplier, income tax, PSID

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^{*} We are grateful for the helpful comments of an anonymous referee. Mary J. Santy provided her usual skill and expertise in manuscript preparation.

1.

Labor Markets With Social Interactions

There are two core research questions in the area of social interactions in the labor market. How do theoretical economic models and their associated econometric representations change when there are social interactions among households? How do policy implications change as the result of estimated households' social interactions? We present a unified theoretical and empirical representation of social interactions as they pertain to labor supply and demand and demonstrate the cases where current policy prescriptions are greatly altered by the presence of social interactions.

We begin by examining theoretically in Section 2 the effect of household interdependencies on how a researcher estimates and subsequently interprets labor supply and earnings equations. We consider two cases: (1) a positive spillover from others' labor supplied and (2) a need for conformity with others' labor supplied. Qualitative and quantitative comparative statics results with a Stone-Geary utility function demonstrate how spillover effects increase labor supply and earnings uniformly. Alternatively, conformity effects move labor supplied toward the mean of the reference group so that, in the limit, labor supply becomes perfectly inelastic at a reference group average labor supplied. When there are un-modeled exogenous social interactions, conventional wage elasticities are still relatively well estimated although structural parameters may not be. Omitting endogenous social interactions may seriously misrepresent the labor supply effects of policy.

Having examined labor supply issues we then turn to the other side of the labor market in Section 3 and give theoretical attention to labor demand. We consider social interactions on the demand side in the context of a two-good economy with the household's demand of one good

influenced by either a spillover effect from other consumers' choices or a conformity effect representing a need for making choices similar to others'. A positive spillover effect increases the demand for the consumer good with interactions, and a conformity effect makes the demand curve for the consumer good pivot around the average market demand to make demand less price sensitive. The collateral implication is that spillover in consumption increases the associated derived demand for labor and conformity in consumption makes the associated derived demand for labor less elastic. We also demonstrate how the presence of a good with social interactions affects the demand for the good without social interactions and the associated demand for the labor producing the no-interactions good. The implied results for the derived demands for labor have meaning for demand-based labor market policy such as the minimum wage, payroll tax, or targeted government expenditures underlying jobs creation programs.

As a further demonstration how the presence of social interactions complicates thinking about economic policy we consider overall labor market outcomes and related economic policy further in Section 4 by examining theoretically the socially optimal wealth distribution. We develop the optimal policy within a two-person two-good model with heterogeneous workers and asymmetric social interactions where only one (social) individual derives positive or negative utility from the leisure of the other (non-social) individual. An outcome is that interdependence might mitigate the need to transfer wealth to low-wage individuals and instead lead them to be poorer by all objective measures. In the presence of social interactions policy to minimize wealth inequality may not be an optimum.

An important aspect of labor market outcomes is how individual and community factors may influence the average length of poverty spells in ways that can enhance the poverty fighting effects of income transfer programs. In Section 5 we measure local economic conditions by the

county unemployment rate and neighborhood spillover effects by the racial makeup and poverty rate of the county. We find that moving an individual from one standard deviation above the mean poverty rate to one standard deviation below the mean poverty rate (from the inner city to the suburbs) lowers the average poverty spell by 20–25 percent; the poverty spillover effect is equal in magnitude to the effect of changing the household head from female to male.

Lastly, we generalize how economic policy issues related to labor market outcomes are changed when there are household social interactions to consider and what we know about the importance of households' labor supply interactions. In particular, in Section 6 we flesh out the econometric details of implementing an empirical model with possible social interactions in labor supply. We look for a response of a person's hours worked to hours worked in the labor market reference group, which includes those with similar age, family structure, and location. We identify endogenous spillovers by instrumenting average hours worked in the reference group with hours worked in neighboring reference groups. Estimates of the canonical labor supply model indicate positive economically important spillovers for adult U.S. men. The estimated total wage elasticity of labor supply is 0.22, where 0.08 is the exogenous wage change effect and 0.14 is the social interactions effect. We demonstrate how ignoring or incorrectly considering social interactions can mis-estimate the labor supply response of tax reform in the United States by as much as 60 percent.

2. Labor Supply With Social Interactions

Ever since the well-known paper on the rat race in the workplace (Akerlof 1976) there has been an increasing interest in how workers interact with each other beyond the indirect market interactions determining wages and labor contracts. Recent models of social interactions in the labor market setting range from a conformity effect (Nakamoto 2009) to envy (Kragl and Schmid 2009). The strong interest in modeling preference interdependence is warranted by both the experimental evidence and empirical research, which point to meaningful and non-negligible social interactions effects in the labor market where workers make interact with multiple motives (Fehr, Goette, and Zehnder 2009). The research shows that because of compensation or status concerns the effort level is strongly affected even if there are no monetary incentives to perform better than co-workers (Falk and Ichino 2006, Mas and Moretti 2009). Our research in the section to follow, first presented in Grodner and Kniesner (2006), examines the potential quantitative labor supply effects of two types of interactions in utility, spillover from others' decisions and conformity with others' decisions.

Social interactions are of much policy relevance for taxation programs or policies directed toward improving the well-being of the unemployed if the social reference group's mean value affects the outcome of interest to the individual (Blomquist 1993). When there are substantial amounts of socially interactive decisions in the form of, for example, positive spillovers, then there will be a social multiplier effect to consider in optimal policy design as individuals react to the actions of others (Becker and Murphy 2000, Glaeser, Sacerdote, and Scheinkman 2002).

Our theoretical research in Grodner and Kniesner (2006) bridges theoretical and econometric considerations in household models where non-ignorable social interactions may be

present. We use the convenient Stone-Geary utility function, which leads to the easily estimable linear earnings function, and demonstrate that even when we introduce a relatively low level of social interaction in utility it can cause an economically significant effect on an individual's labor supply (and consumption). Ignoring social interactions can cause a serious bias on the estimated structural (utility function) parameters of interest. We also identify situations when other economic concepts that depend on combinations of biased structural parameters, such as labor supply/consumption derivatives and elasticities, may or may not be accurately estimated. The shifts of the labor supply function are general qualitatively for any utility function with imbedded social utility components and with leisure as a normal good (Grodner 2003); the calibrated Stone-Geary utility function lets us quantify the results.

2.1 Theoretical Framework

We build on the a flexible treatment of social interactions formulated by Brock and Durlauf (2001a,b), where interactions enter into a model with total utility, $V(\bullet)$, encompassing a social utility term, $S(\bullet)$, and individual utility term, $u(\bullet)$:

$$V=V(u(\bullet),S(\bullet)) \tag{2.1}$$

Our starting point is the model without interactions (baseline, without $S(\bullet)$); we then discuss forms of interdependence.

Our focus throughout is on labor supply using the Stone-Geary utility function. The Stone-Geary has convenient properties for estimating labor supply and consumption expenditures. Because the earnings function is linear in the wage rate and non-labor income, w and Y , and the associated labor supply function is linear in $1/w$ and Y/w , similar social

interactions effects appear in other widely used utility functions (Stern 1986).¹ The Stone-Geary has also been shown to be a convenient functional form for studying issues related to intertemporal substitution and risk sharing (Ogaki and Zhang 2001, Low 2005, Low and Maldoom 2004). Stone-Geary utility easily admits social interactions in a natural way through its structural parameters. Kooreman and Schoonbeek (2004) and Abel (2005) prove conditions for the existence of welfare improvements over the market equilibrium case with interdependence and the implied optimal taxes that mitigate negative effects of social interactions.

We begin with the baseline utility function without interactions:

$$U(h, c) = \theta \ln(\gamma_h - h) + (1 - \theta) \ln(c - \gamma_c) \quad (2.2)$$

$$st. c \leq wh + Y, 0 < \theta < 1,$$

where c is consumption, h is hours worked, θ is the expenditure share on leisure ($l = T - h$, with l being leisure and T being total hours available), γ_h is the level of maximum feasible hours of work, and γ_c is the minimum necessary commodity consumption.

An econometric advantage of the Stone-Geary (2.2) is that after maximizing utility with respect to consumption and labor supplied the optimal hours worked imply that earnings are linear in both the variables and parameters (Abbott and Ashenfelter 1976):

$$wh = (\theta\gamma_c) + (\gamma_h(1 - \theta))w + (-\theta)Y = \beta_0 + \beta_w w + \beta_Y Y. \quad (2.3)$$

The three parameters of the utility function are exactly identified as estimates of $(\beta_0, \beta_w, \beta_Y)$ reveal $(\theta, \gamma_h, \gamma_c)$. We will refer to the earnings function in (2.3) as the Stone-Geary

1. Obvious ones are utility and labor supply functions linear in $[w, Y]$, $[\ln w, \ln Y]$, or $[w, w^2, Y, Y^2, (wY)]$.

without interactions or, more simply, as the baseline model, which is always the point of comparison. The wage effect on labor supply in our benchmark case is

$$\partial h / \partial w = \frac{(1-\theta)\gamma_h - h}{w}. \quad (2.4)$$

Because the models quickly become complicated, most theoretical studies involving social interactions use a specific functional form, which can still permit quite general conclusions about social interaction effects (Bernheim 1994, Akerlof 1997, Akerlof and Kranton 2000). The Stone-Geary utility function encompasses much of the previous theoretical research on social interactions and is a convenient objective function for introducing social interactions in a theoretically satisfactory way. We follow the approach known as demographic translating where the demographic characteristics of the individuals reside inside the parameter representing the limit value for hours of work, γ_h (Pollak and Wales 1992).

2.2 Spillover Effects

We embed the social utility (spillover) effect into the parameter γ_h' , using the specification suggested by Brock and Durlauf (2001a,b), $\gamma_h(S(\bullet))' = \gamma_h + \alpha_1 h \mu_h$, where μ_h is the expectation (perhaps sample mean) of hours worked by the reference group members. The reference group is any set of other individuals in the population to which the person refers when making a labor supply decision. The parameter α_1 represents the importance of social utility (spillover) to the individual so that now

$$U(h, c; \mu_h) = \theta \ln(\gamma_h + \alpha_1 \mu_h h - h) + (1-\theta) \ln(c - \gamma_c). \quad (2.5)$$

The spillover effect can be viewed as a positive externality generated by the labor supplied in the reference group, where a higher mean of hours worked in the reference group

decreases the individual's disutility from working. An obvious way to interpret the spillover effect is that someone feels less pain from working if he or she knows others also work.²

Maximizing (2.5) with respect to c and h yields the augmented earnings function

$$wh = \frac{\{\gamma_c \theta\} + \{\gamma_h (1 - \theta) w\} + \{-\theta Y\} - (\gamma_c \theta \alpha_1) \mu_h + (\theta \alpha_1) \mu_h Y}{(1 - \alpha_1 \mu_h)}. \quad (2.6)$$

The curly brackets $\{\}$ contain terms from the baseline model. Note that the addition of spillover effects adds two variables to the earnings equation, μ_h and $\mu_h Y$, makes the earnings equation nonlinear, and over-identifies the parameters.

When the base utility function is Stone-Geary incorporating spillovers from others' work efforts, the wage effect on labor supply is

$$\partial h / \partial w = \frac{\{\gamma_h (1 - \theta) - h\} + \alpha_1 \mu_h h}{\{w\} - \alpha_1 \mu_h w}. \quad (2.7)$$

Note that $\partial^2 h / \partial w \partial \alpha_1 \geq 0$ so that labor supply spillover effects make the individual's response to the wage more positive than in the absence of spillovers. For the interested reader a game-theoretic justification for social norms in consumption appears in Young (1998) and Soetevent and Kooreman (2002).

2. Such a positive externality is recognized in different contexts in social psychology. Under the rule of reciprocation one feels equally deserving of outcomes in the reference group (Cialdini 1993). In cultural spillover the more society legitimates long work hours the more people work to gain social approval (Baron and Straus 1989). In behavioral therapy a person feels relief from trauma when he or she knows that others had similar negative experiences (Hawkins and Eagger 1999).

2.3 Conformity Effects

Conformity in behavior and attitudes is a fundamental concept in social psychology (Sherif 1935). The general idea is that individuals tend to conform to broadly defined social norms and the magnitude of response depends on cohesiveness, group size, and social support.³

Again, we embed the interdependence via the parameter γ_h of the baseline utility function so that $\gamma_h(S(\bullet)) = \gamma_h - (\alpha_2/2)(h - \mu_h)^2$. Augmented utility is

$$U(h, c; \mu_h) = \theta \ln(\gamma_h - \frac{\alpha_2}{2}(h - \mu_h)^2 - h) + (1 - \theta) \ln(c - \gamma_c). \quad (2.8)$$

The practical implication of a conformity effect in utility is that the person feels penalized when working a different amount of hours than what is typical for the reference group.

Intuitively, because there is a penalty for differing from the conformity value for h , the utility function incorporating conformity in (2.8) should have a smoothing effect on hours relative to the baseline model. The smoothing effect of conformity should in turn mean that a change in h will have a smaller effect on utility than in the baseline case with an accompanying regression toward the group mean.

The augmented earnings function with a conformity effect is

$$wh = \frac{\{\theta\gamma_c\} + \{\gamma_h(1 - \theta)w\} + \{-\theta Y\} + \gamma_c\theta\alpha_2(h - \mu_h) - \theta\alpha_2(h - \mu_h)Y + \frac{\alpha_2}{2}(\theta - 1)\mu_h^2 w}{(1 - \alpha_2\mu_h + (1 + \theta)\frac{\alpha_2}{2}h)}. \quad (2.9)$$

In the case of conformity the spillover effect introduced into the earnings function via the presence of μ_h is replaced by $(h - \mu_h)$. Again, the conformity version of the earning function is non-linear, but now more complicated in that there is not a simple (linear) closed-form solution

3. For an interesting discussion of the costs and benefits to society of conformity versus non-conformity see Sunstein (2002).

for either earnings or hours of work. The underlying fundamental parameters are again over-identified as there are more interaction terms and non-linearity due to the presence of both the individual's labor supplied and the reference group's average hours worked.

The wage effect on labor supply when there is a conformity effect is

$$\frac{\partial h}{\partial w} = \frac{\{(1-\theta)\gamma_h - h\} + \frac{\alpha_2}{2}(h - \mu_h)((1+\theta)\mu_h - (1-\theta)h)}{\{w\} + \theta\alpha_2(Y - \gamma_c) + w\alpha_2((1+\theta)h - \mu_h)}, \quad (2.10)$$

where the terms in curly brackets { } again indicate the basic Stone-Geary model.

Even in the Stone-Geary case the expression for the effect of the wage on labor supplied is lengthy, and without specific assumptions it is impossible to determine the labor supply function effects of conformity compared with the baseline case.

2.4 Stone-Geary Utility and Linear Expenditure System with Interactions

Earlier we noted that the Stone-Geary utility function is convenient for its simplicity and relative flexibility. However, most research that includes social interactions into the LES does not distinguish among different forms of interactions, such as spillover versus conformity, and the interactions are not modeled as related to the individual's demand for the particular good.

Using the notation we introduced earlier, most research implicitly uses $S = S(\alpha, \mu_h) = \alpha\mu_h$. Our work can then be viewed as an extension of the LES with interactions where the individual's choice affects the level at which one responds to the choices of others. Our extension is reasonable because we contend that people are more likely to care about the actions of others in their reference group if the particular activity makes a significant contribution to the individual's utility. Here we take $S(\alpha, h, \mu_h) = \alpha h\mu_h$ for the particular case of spillover and

$S(\alpha, h, \mu_h) = (\alpha/2)(h - \mu_h)^2$ for the particular case of conformity. The most common LES model with interactions to date, which uses $S(\alpha, \mu_h) = \alpha\mu_h$, then closely resembles our spillover effect.

Finally, in further relation to the past literature on the LES with interactions we also distinguish between exogenous and endogenous interactions as represented by the presence of μ_h . By considering endogeneity as an issue we attempt to include the concept of a social multiplier into a popular parametric utility specification used in studies of interdependence in consumption and labor supply.

2.5 Exogenous Social Interactions

We now present the details of labor supply with versus without social interactions in utility. We first compute the basic Stone-Geary utility function and then add spillover or conformity. Last we compute the labor supply functions and elasticities. The end product is an enhanced understanding of the relative effect of social interactions in the individual's preferences on the labor supply outcomes. The conclusions in the following sections concerning spillover and conformity are general in that only the magnitudes differ for various functional forms (Grodner 2003). We select the Stone-Geary utility function form mainly for tractability.

2.6 How Social Interactions Shift Labor Supply

We begin by creating results comparable to Blomquist (1993) who computes hours of work for given wage rates and selected magnitudes of interactions. The values for hours of work we will discuss have been computed using the solutions for desired h from the three earnings functions, (2.3), (2.6), and (2.9), with numerical details described. In the case of the baseline model versus spillover, computing labor supply is a straightforward manipulation of the earnings function. In the case of the baseline versus conformity, deriving labor supply involves the solution to the quadratic function for earnings with respect to h .

2.6.1 Calibration

To begin, we need values for the parameters of the utility function: γ_h (maximum feasible hours of work), γ_c (minimum necessary consumption), θ (proportion of full income implicitly spent on leisure), and the moments of the distributions for the independent variables: Y (non-labor income) and w (hourly wage). We calibrate the model using data from a well-known econometric study that examines the Stone-Geary based labor supply model (Abbott and Ashenfelter 1976, 1979).

Here $\theta = 0.113$ based on our own regression estimates with the data of Abbott and Ashenfelter. Our other econometric parameter estimates include minimum consumption, $\gamma_c = 636$, and maximum hours of work, $\gamma_h = 2465$. The remaining calibration values we use are the mean of annual hours of work needed for spillover and conformity effects in labor supply, $\bar{h} \equiv \mu_h = 2172$, and the sample means (\$1967) of non-labor income, $\bar{Y} = \$733$, and the hourly wage rate, $\bar{w} = \$0.77$. Note that 2172 is not the exact mean of hours worked in the data, but rather hours worked at the mean wage and mean non-labor income using our estimation results from the Stone-Geary earnings function. We force labor supply through the mean hours worked at the mean wage rate, which the earnings function itself need not do. Finally, note that the slope of labor supply is positive here.

The three labor supply functions that we examine numerically are

Baseline (rearranged equation (2.3))

$$h = \frac{\theta\gamma_c}{w} + (1-\theta)\gamma_h - \frac{\theta Y}{w}. \quad (2.11)$$

Spillover (rearranged equation (2.6))

$$h = \frac{\{\gamma_c \theta + \gamma_h (1 - \theta) w\} - \{\theta Y\} + (\gamma_c - Y) \theta \alpha_1 \mu_h}{\{w\} (1 - \alpha_1 \mu_h)}. \quad (2.12)$$

Conformity (positive value after finding the solution to the quadratic equation in (2.9))

$$h = \frac{1}{2a} (-b - \sqrt{b^2 + 4ac}), \quad (2.13)$$

where

$$a = \frac{\alpha_2}{2} \{w\} (1 + \theta)$$

$$b = (w(\alpha_2 \mu_h - 1) + \alpha_2 \gamma_c \theta - \alpha_2 \{\theta Y\})$$

$$c = [\{w(1 - \theta) \gamma_h\} - \frac{\alpha_2}{2} \mu_h^2 w (1 - \theta) + \{\theta(Y - \gamma_c)\} (\alpha_2 \mu_h - 1)]$$

We compute results for the two different interactions specifications with differing magnitudes of spillover and conformity effects as represented by the numerical value for the parameter α_i . For simplicity we use $\alpha_1 = 0.00001$ to represent a small amount of spillover and (double it to) $\alpha_1 = 0.00002$ to represent much greater spillover.⁴ For comparability we consider results for low versus high conformity effects, $\alpha_2 = 0.005$, and twice its value, $\alpha_2 = 0.01$.⁵ It is important to recognize that α_1 and α_2 are not connected; they are totally different parameters governing two separate models of social interactions.

To understand labor supply with social interactions we present our results graphically. Figure 2.1 shows that spillover creates mostly a parallel rightward shift in the labor supply function where the magnitude of the shift depends on the value of α_1 . Spillover leads to more

4. A small value for α_1 is close to 0; the limiting value is $1/2172 = 0.00046$ because leisure is a normal good.

5. Here a small value for α_2 is again close to zero, but there is no obvious maximum.

labor supplied and a similar wage responsiveness of labor supply with and without spillover.⁶ Figure 2.2 illustrates that conformity causes labor supplied to tend toward the mean of the reference group, μ_h . Workers with $h < \mu_h$ in the absence of conformity work more hours under conformity, and workers with $h > \mu_h$ in the absence of conformity work fewer hours under conformity. As the importance of conformity in the utility function (α_2) rises, labor supply becomes steeper and less elastic. The conclusions for both spillover and conformity are general in that only the magnitudes differ for various functional forms (Grodner 2003, Grodner and Kniesner 2006, Appendix A).

2.7 Estimation Bias When Spillover Is Present But Ignored

To determine the effect of the unmodeled social interactions in a hypothetical empirical study we first need to consider what kind of data and estimator are to be used. As a starting point it seems reasonable to assume that the norms individuals refer to may be related to behavior (a) of their own in the past (time series), (b) of other individuals in the present (cross-section), or (c) both (panel data). If the levels of the norms vary across individuals, it means that μ_h from (2.5) or (8) may be group-specific or even individual specific. Each case would require a specific data set and the appropriate estimation technique.

One interesting example is the case of the family members being the reference group for each other (Neumark and Postlewaite 1998). The idea has both theoretical foundation and reasonably good quality data available for testing it. In a family reference group situation the model would be similar to the approach used in studies of the Rotten Kid Theorem (Becker

6. Notice that the point elasticity changes because the person chooses higher hours of work at a given wage.

1981). One of the model's predictions is that dividing income equally is usually not family welfare maximizing. In our setup we would consider the effect of the overall family non-work time on each individual's labor supply. The difficulty of the research would be in identifying the effect of the social interaction from the effect of the public good in the household due to the benefits of living together. In his review article Bergstrom (1997) discusses how interactions within the family can affect the behavior of the individuals in the household, Jenkins and Osberg (2003) investigate social interactions within the family as a leisure coordination problem, and Alesina, Glaeser, and Sacerdote (2005) find that Europeans may work less than Americans because of regulations that enable Europeans to take vacations at the same time, which raises the satisfaction from vacations and induces more vacation time.

In the following discussion we assume the simplest possibility: the same norm for every person. It is the most basic case relevant for the cross-sectional data. Although constant μ_h may be unrealistic, it is instructive and relatively easy to examine.

When the reference group is the population the relevant comparison point is μ_h , which is the same for every person. Because there is no variation in the reference group in our simple example, μ_h becomes another parameter in the utility function, so we call it a distorted Stone-Geary. The system in terms of the structural parameters is exactly identified, so the linear labor earnings equation with spillover (2.6) is

$$wh = \{\gamma_c \theta\} + \left(\frac{\{\gamma_h (1 - \theta) w\}}{(1 - \alpha_1 \mu_h)} \right) - \{\theta Y\}. \quad (2.14)$$

From (2.14) we see that a consequence of ignoring positive spillover and estimating the linear earnings regression in (2.3) versus the correct non-linear earnings function in (2.14) is an upward bias in the coefficient of the wage, β_w , by $1/(1 - \alpha_1 \mu_h)$. Ignoring positive spillovers in

turn produces an upward bias in $\hat{\gamma}_h = (\hat{\beta}_w / (1 + \hat{\beta}_y)) = \gamma_h / (1 - \alpha_1 \mu_h)$ because $0 < (1 - \alpha_1 \mu_h) < 1$.⁷

When the spillover in hours is ignored incorrectly two of the structural parameters are correctly estimated as $E(\hat{\theta} - \theta) = 0$, $E(\hat{\gamma}_c - \gamma_c) = 0$. The third is not since $E(\hat{\gamma}_h - \gamma_h) = (\alpha_1 \mu_h / (1 - \alpha_1 \mu_h))$ is the proportional upward bias in the estimated value of γ_h .

Note that replacing $\hat{\gamma}_h$ with the estimated value of $\gamma_h / (1 - \alpha_1 \mu_h)$ in the slope of the baseline model yields

$$\left(\frac{\partial h}{\partial w} \right)_{\text{misspecified baseline}} = \frac{\hat{\gamma}_h (1 - \hat{\theta}) - h}{w} = \frac{\frac{\gamma_h}{(1 - \alpha_1 \mu_h)} (1 - \theta) - h}{w} = \left(\frac{\partial h}{\partial w} \right)_{\text{correct spillover}}. \quad (2.15)$$

As long as the researcher uses the correct slope formula implied by the assumed model, even incorrectly omitting spillover need not affect a result of interest. The baseline earnings function approximates the spillover model.

Unbiasedness of $\hat{\beta}_0$ and $\hat{\beta}_y$ extends to other earnings/labor supply functions when the estimated coefficients are not a function of γ_h . When spillover does not have a linear form then all coefficients can be biased in undetermined ways (Grodner 2003).

2.8 Estimation Bias When Conformity Is Present But Ignored

When there is a conformity effect we cannot solve for the bias in the structural parameters inferred from the estimated regression coefficients of a linear labor earnings function ignoring social interactions. The difficulty in establishing bias analytically happens because the

7. Another way to view the issue is that if γ_h varies across individuals due to the presence of μ_h but γ_h is treated as a constant we have what amounts to an incorrectly specified random parameters model.

conformity case (2.9) cannot be solved explicitly for earnings, and the associated labor supply function (2.12) is non-linear in the wage and non-labor income.

From Figure 2.2 we can deduce the bias to the coefficients in the labor supply or earnings functions. Because we know that conformity makes labor supply flatter the dependent variable, hours of work, has less variation. In the limit labor supply becomes constant. As a consequence, all coefficients that are not a function of γ_h will be zero. In the particular case of the Stone-Geary earnings function $\hat{\beta}_0 \rightarrow 0$, $\hat{\beta}_Y \rightarrow 0$, and $\hat{\beta}_w \rightarrow \mu_h$. The inferred structural parameters will also be biased in that $\hat{\theta} \rightarrow 0$, $\hat{\gamma}_c \rightarrow 0$, and $\hat{\gamma}_h \rightarrow \mu_h$.

2.9 Summary: Estimation Bias From Ignoring Exogenous Social Interaction

The fact that the bias to the baseline coefficients is different when spillover or conformity effects are present, but ignored, underlines the need for a precise modeling of interactions effects. For example, a researcher cannot simply include μ_h into the regression to control for the omitted variable bias. If the interactions are exogenous, though, we believe that using a so-called partly linear regression model will suffice to control for social interactions of unknown functional form (Yatchew 2003).

So far our discussion has taken the expectation of hours worked for others in the individual's reference group, μ_h , as an exogenous social norm. The consequence of the social norm interpretation is that social interactions are effectively a response by the individual to the labor supply of the reference group. The difficulty of estimating labor supply with exogenous social interactions comes from the likelihood that the researcher does not know what μ_h is for an individual (omitted variable bias) or mis-specifies how μ_h enters the labor supply function algebraically (incorrect functional form bias). We have demonstrated how the presence of

exogenous positive spillover social interactions shifts out the labor supply schedule and how exogenous conformity social interactions pivots labor supply to approach a constant hours worked that is the group norm. Now we consider what happens to labor supply when μ_h is endogenous.

2.10 Endogenous Social Interactions and Economic Policy

For the intuition behind an endogenous μ_h consider a worker who, in addition to being directly affected by the social norm in the reference group (in the form of average hours worked), now can also affect the social norm by changing labor supplied (which in turn affects reference group average hours worked). In addition to the direct wage effect there is also an indirect effect through feedback from the other $(n-1)$ members of the reference group. Because it is the case that $\mu_h = \bar{h}_{-i} = \sum_{j=1, i \neq j}^n h_j / (n-1)$ the labor supply model within each reference group becomes a simultaneous system as the labor supply of each member enters into the labor supply of all other members. Now the interactions no longer depend on an exogenous social norm, but rather on an endogenous social norm that is jointly determined by all the members of the reference group. Practically speaking, μ_h becomes an endogenous variable such that an increase in the labor supply of each reference group member increases the mean hours worked in the reference group, and when the other members of the group respond to the change of the overall mean there is a feedback effect to the person who initially changed labor supply.

There are two situations to consider: (a) only the individual's wage changes and (b) the wage change is general to the reference group such that each member experiences the same wage change. The size of the reference group also plays a crucial role concerning the wage effects in the two situations of person-specific versus group-wide wage changes. With person-specific

wage effects, $\partial \bar{h}_{-i} / \partial h_i \rightarrow 0$ as n increases so that in large groups the endogenous feedback effect is negligible and can be ignored in evaluating the labor supply effects of policies that alter the wage.⁸ Group-wide wage effects make the researcher consider, however, that

$$\partial h_i / \partial w_i = (\partial h_i / \partial w_i) |_{\bar{h}_{-i}} + (\partial h_i / \partial \bar{h}_{-i})(\partial \bar{h}_{-i} / \partial w_i). \quad (2.16)$$

Represented more completely in a schematic the social interactions process looks like

$$\underbrace{w_i \rightarrow h_i}_{(\partial h_i / \partial w_i) |_{\bar{h}_{-i}}} \xrightarrow{(\partial \bar{h}_{-i} / \partial w_i)} \underbrace{\bar{h}_{-i} \rightarrow h_i^1 \rightarrow \bar{h}_{-i}^1 \rightarrow \dots \rightarrow h_i^e}_{(\partial h_i / \partial \bar{h}_{-i})}. \quad (2.17)$$

When the interactions are exogenous $\partial \bar{h}_{-i} / \partial h_i = 0$; changes in individual hours worked do not affect average hours worked because average hours worked are at the norm. When the interactions are endogenous and there is only an individual's wage change, $\partial \bar{h}_{-i} / \partial h_i \neq 0$ due to the feedback effect, but $\partial \bar{h}_{-i} / \partial h_i$ tends to zero as the number of reference group members increases (Glaeser, Sacerdote, and Scheinkman 2002). With both exogenous and endogenous interactions and an individual wage change, the wage causes only a $(\partial h_i / \partial w_i) |_{\bar{h}_{-i}}$ change in hours worked because \bar{h}_{-i} does not change (much) so that we have exogeneity in the sense of no observable feedback effect for large groups.

When the interactions are endogenous and $(\partial \bar{h}_{-i} / \partial h_i)$ is non-negligible the individual experiences not only an exogenous effect that is $(\partial h_i / \partial w_i) |_{\bar{h}_{-i}}$ but also an endogenous effect that is $(\partial h_i / \partial \bar{h}_{-i})(\partial \bar{h}_{-i} / \partial w_i)$. The schematic in (2.17) emphasizes that an endogenous effect is first

8. Specifically, \bar{h}_{-i} is a weighted mean with weights $1/n$, and in larger groups an individual's contribution of h_i to \bar{h}_{-i} ($\forall j \neq i$) is negligible because $(1/n) \rightarrow 0$ as $n \rightarrow \infty$.

triggered by the exogenous change in the wage rate $(\partial \bar{h}_{-i} / \partial w_i)$, and then the endogenous change continues on its own through the circular feedback effects $(\partial h_i / \partial \bar{h}_{-i})$ until the labor market reaches an equilibrium hours worked, h_i^e .⁹

One way to have a non-negligible $\partial \bar{h}_{-i} / \partial h_i$, which makes endogenous social interactions matter, is when there is a general wage change so that each person experiences the same Δw_i . Even a small Δw_i can generate a significant aggregate effect on hours worked, Δh_i . Therefore, \bar{h}_{-i} for each person will initially change by exactly Δh_i , and the effect $\partial \bar{h}_{-i} / \partial h_i$ will no longer be negligible. An increase in the number of reference group members means that $\partial \bar{h}_{-i} / \partial h_i$ decreases for each person because it is distributed across more workers, in turn making the aggregate effect, $\partial \bar{h}_{-i} / \partial h_i$, the same no matter what n is. Regardless of the size of the reference group the labor supply effect through $\partial \bar{h}_{-i} / \partial h_i$ will be the same for a given Δw_i . If we represent aggregate changes in terms of the changes in the average hours worked and average wage, the total effect is

$$(\partial \bar{h} / \partial \bar{w}) = (\partial h / \partial w)|_{h=\bar{h}, w=\bar{w}} + ((\partial h / \partial \bar{h})|_{h=\bar{h}})(\partial \bar{h} / \partial w)|_{w=\bar{w}}.^{10} \quad (2.18)$$

9. There are certain additional conditions that need be satisfied for existence, uniqueness, and stability of equilibrium. The explicit Stone-Geary utility function guarantees a unique stable equilibrium. For more discussion see Brock and Durlauf (2001b).

10. As a practical note, in our simulations we first compute $\partial h / \partial w|_{h=\bar{h}, w=\bar{w}}$ by taking μ_h as constant, calculating $\partial h / \partial w$, and then setting $\mu_h = \bar{h}$. We also compute $\partial \bar{h} / \partial \bar{w}$ by first setting $\mu_h = \bar{h}$, then taking $\partial \bar{h} / \partial \bar{w}$. Thus, the total effect on the left-hand side of (2.16) and the

Up to now we have considered the first term in (2.16) compared to a model that incorrectly ignores exogenous social interactions (equations (2.11)–(2.13) and Figures 2.1 and 2.2). We now turn our attention to the two specific algebraic forms of (2.16) capturing spillover and conformity. In particular, we numerically examine the relative size of the total effect $\partial \bar{h} / \partial \bar{w}$ and the exogenous effect $(\partial h / \partial w)_{h=\bar{h}, w=\bar{w}}$ in (2.16), which reveals by how much the labor supply wage effect differs when one now considers group-wide wage changes that alter the labor supply reference point for the individual.

In what follows we compute $m = (\partial \bar{h} / \partial \bar{w}) / (\partial h / \partial w)_{h=\bar{h}, w=\bar{w}}$, which is sometimes called a social multiplier because it measures how much the total change differs from the exogenous change due to an exogenous shock (Becker and Murphy 2000, Glaeser et al. 2003). When there are no interactions or interactions are exogenous the social multiplier equals 1. The multiplier also connects labor supply elasticities as: $\eta(\textit{endogenous}) = m \times \eta(\textit{exogenous})$.

Empirically it is critical to identify the social multiplier because a researcher can estimate only $\eta(\textit{exogenous})$ correctly (Aronsson et al. 1999). A researcher can control for exogenous interactions by including a nonlinear function for μ_h . For endogenous interactions, one not only needs a nonlinear function of μ_h but also must worry about the endogeneity of μ_h and the degree of the feedback effect.

exogenous effect in the first term on the right-hand side are only the same when either $\mu_h = 0$ or $\alpha_i = 0$. Note also that (2.16) is a particular form of the decomposition introduced by Becker and Murphy (2000, p. 13) for a demand for goods and services.

2.11 The Wage Effect When the Spillover Effect Is Endogenous

In the case of spillover with Stone-Geary utility, the social multiplier with endogenous social interaction is

$$m = \frac{\partial \bar{h} / \partial \bar{w}}{(\partial h / \partial w) \Big|_{h=\bar{h}, w=\bar{w}}} = \frac{\frac{(1-\theta)\gamma_h - \bar{h} + h^2\alpha_1}{\bar{w} - 2\bar{w}\alpha_1\bar{h} - \theta\alpha_1(Y - \gamma_c)}}{\frac{(1-\theta)\gamma_c - \bar{h} + h^2\alpha_1}{\bar{w} - \bar{w}\alpha_1\bar{h}}} = \frac{\bar{w}(1 - \alpha_1\bar{h})}{\bar{w}(1 - \alpha_1\bar{h}) - \alpha_1(\bar{w}\bar{h} + \theta(Y - \gamma_c))}. \quad (2.19)$$

We have numerically simulated the labor supply implications of different levels of the spillover effect (α_1). The social multiplier when there is endogenous spillover increases with the level of interactions, and the increase becomes more than proportional for high levels of interactions, which suggests that the feedback effect works longer or the changes are larger. For spillovers where $\alpha_1 = 0.00001$ the wage effect is about two percent greater when spillover effects are endogenous; when the spillover importance increases 10 times to where $\alpha_1 = 0.0001$, the wage effect is 40 percent (or about 20 times) larger when spillover effects are endogenous.

It is helpful to reinforce the social multiplier under social interactions by considering it graphically in Figure 2.3. When we consider the shift of the labor demand curve from D_0 to D_1 , the equilibrium moves from point A to point B (exogenous change: $h_B - h_A$) and then from point B to point C (endogenous change: $h_C - h_B$). The endogenous change comes from the fact that the exogenous change increased equilibrium labor supply to h_B and so the reference hours worked μ_h increased also (feedback effect). Absent exogenous social interactions labor market equilibrium would be at P.

Our measure of the importance of endogenous social interactions in (2.17), which represents by how much higher the effect of the wage change on the labor supply is when interactions are endogenous than when the interactions are exogenous, is essentially the ratio of the total change to the exogenous change in hours worked, or $(h_C - h_A)/(h_B - h_A)$ in Figure 2.3.

Moreover, if one uses individual data and does not control for interactions, one will incorrectly observe total change as to h_B (multiplier = 1). On the other hand, if one uses aggregate data, one observes correctly the total change as to h_C . The logic follows Glaeser et al. (2003) who demonstrate both theoretically and empirically that the level of aggregation can reveal the existence of social interactions in the data. Our discussion also formalizes a point made by Blomquist (1993) who notes that the researcher needs to consider the effect of interdependence when data are disaggregated.¹¹

2.12 The Wage Effect When the Conformity Effect Is Endogenous

When there is conformity in the Stone-Geary case the social multiplier with endogenous social interaction is

$$\frac{\partial \bar{h}_i / \partial \bar{w}}{(\partial h_i / \partial w) \Big|_{\substack{h=\bar{h} \\ w=\bar{w}}}} = \frac{\frac{(1-\theta)\gamma_h - \bar{h}}{\bar{w}}}{\frac{\{(1-\theta)\gamma_h - \bar{h}\} + \frac{\alpha_2}{\bar{w}}(\bar{h} - \bar{h})(1+\theta)\bar{h} - (1-\theta)\bar{h}}{\{\bar{w}\} + \theta\alpha_2(Y - \gamma_c) + \bar{w}\alpha_2((1+\theta)\bar{h} - \bar{h})}} = 1 + \frac{\alpha_2\theta(Y - \gamma_c + \bar{w}\bar{h})}{\bar{w}}. \quad (2.20)$$

We have numerically simulated the labor supply implications of various levels of the conformity effect (α_2). We find that proportionate increases in α_2 match proportionate increases in the social multiplier. The social multiplier under endogenous conformity increases proportionally with the level of interactions largely because the wage effect with endogenous conformity does not depend on α_2 .

11. The multiplier computed in Glaeser et al. (2003) at different levels of aggregation can be interpreted in our framework as if only part of the population experienced an exogenous wage change, and the researcher observes the equilibrium somewhere between B and C. When the entire population has the exogenous wage change the multiplier in Glaeser et al. coincides with our total change multiplier so that our result extends theirs.

2.13 Implications for Research and Policy

In the presence of endogenous social interaction effects there are two components of the change in hours worked due to a wage change. The first component of interactions is exogenous, which increases the labor supply effect due to the wage changes relative to the situation with no social interactions. The second component is due to the endogeneity of μ_h , which further increases the wage effect. The total wage effect that includes endogenous spillover may be large relative to the baseline case of no social interactions, and the bias in labor supply wage effects may be even larger from ignoring social interactions. If the ultimate goal is to use structural parameters of labor supply in simulations of policy, such as income tax reforms, the researcher investigating social interaction effects empirically needs to determine not only whether social interactions are present but also whether they are exogenous or endogenous. When interactions are exogenous the results from a mis-specified model can still be useful for policy evaluations. When interactions are endogenous the results from a mis-specified model can be quite misleading because the researcher cannot correctly identify elasticities (See Aronsson, Blomquist, and Sacklén 1999 for an example). The result is more important because even the introduction of a flexible functional form will not solve the problem. Not taking into account the multiplier will likely understate the true effect.

If there are exogenous social interactions the individual wage effect will be higher for spillover but the elasticity can be well estimated. If spillovers become endogenous the wage effect on labor supply will be higher than when spillovers are exogenous although the implications for relative point elasticities are unclear. When there is exogenous conformity the wage effects become smaller. Practically speaking, when there are social interactions in the form

of spillover there is an externality effect that makes behavioral responses to any policy induced wage change stronger. Endogeneity of spillovers further strengthens the policy impact.

Considering all the theoretical implications of social interactions, to make reliable inferences for policy evaluations a researcher must still decide which behavioral effects to use in the particular situation. Ideally the researcher concerned with labor supply-wage issues would want to have the correct individual effect, $(\partial h / \partial w)^{indiv}$, along with the social interactions effect, $(\partial h / \partial \mu_h)^{social}$, to reveal the total effect, $(\partial h / \partial w)^{total}$. However, decomposing the total wage effect into its two components may be infeasible because the researcher may not know the functional form for social interactions or whether they are exogenous or endogenous.

2.14 Summary

Our research has provided evidence concerning the possible bias in estimating labor supply that may stem from the situation where there are un-modeled social interactions present. We considered cases of positive spillover and conformity in hours worked both analytically and numerically. The social interaction effects and their consequences we identify are relevant not only for social interactions in labor supply but also for social interactions in consumer demand, particularly for the Stone-Geary based linear goods and services expenditures and labor earnings system.

The results that there is a positive shift of labor supply due to spillover and a pivoting of the labor supply schedule due to conformity are relatively general for concave utility functions with two goods and most likely in models with many goods as well (Grodner 2003; Grodner and Kniesner 2006, Appendix A). Depending on the functional form of utility and the social utility term the exact changes in the labor supply schedule due to social interactions may differ, although the general patterns remain as we present. Calibration and usage of the popular Stone-

Geary utility function lets us connect the ideas of social interactions to the empirical studies in the literature, relate our work to past research on the LES with interactions, and underline the economic significance of different forms and levels of interdependence. The implications of interactions related to specific functional forms of social utility extend to other theoretical specifications of total utility.

Our results suggest that the bias in the parameters of interest from ignoring social interactions can be economically significant and will differ depending on the form and magnitude of the interactions. Even if one correctly knows the reference group for each individual, adding the reference group's mean hours of work to the regressor list may not be enough to control for the presence of social interactions because the mean hours of work for the reference group may enter non-linearly. Still, something can be learned about the form of social interactions if the researcher can compare results of a badly mis-specified model with the true or closer-to-true model. For example, if the mis-specified model fits the data well then the relative parameters, such as elasticity, can still be accurately estimated.

When there are unmodeled exogenous interactions the estimated structural parameters are biased but elasticities are well estimated. The potential solution is a flexible functional form. However, when interactions are endogenous both parameters and elasticities are incorrect. The possible solution is not only a flexible functional form but also a way to estimate the multiplier. Testing for endogenous versus exogenous interactions and specific solutions are fruitful topics for future research.

We contend that because a researcher usually uses micro data for demand or supply estimation our insights are of interest to those involved in applied microeconomic studies where social interaction may be present. We have also demonstrated that our work connects to as well

as extends established results in the literature and have developed more generally the concept of the social multiplier.

There are different effects on labor supply generated by the different forms that social interactions may take. There is sometimes confusion among economists about the exact meaning of concepts acquired from other disciplines (Manski 2000), and sometimes economists are not clear that the broad term social interactions may encompass many different types of behavior. We have attempted to demonstrate the important differences between endogenous and exogenous spillover versus exogenous and endogenous conformity effects in labor supply. The discussion highlights the research value added from specifying correctly what type of interaction may be present. Our results also warn the applied researcher against using a common econometric specification of interaction effects where the reference group mean is simply included as an additional regressor. Finally, our results also imply the benefits of trying to identify the correct type of interaction.

Additional Reading

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3. Social Interactions in Commodity and Derived Labor Demands

Social interactions are of much policy relevance because they can alter the effects of taxation or transfer programs intended to improve the economic situation of the poor or unemployed (Grodner and Kniesner 2006, 2008a). If there are significant interactions then optimal policy need consider the synergies described by so-called social multiplier effects. Where workers care about their positions in the income distribution then a beneficial regulatory policy that does not alter relative incomes receives too low a benefit in conventional cost-benefit calculations. Thus, ignoring social interactions can mis-state significantly the social welfare effects of taxes, transfers, or regulatory policy.

Our contribution in Grodner and Kniesner (2008a) is an increased understanding of the role of social interactions is to flesh out succinctly the demand implications of two basic forms of interactions: spillover (externality from other consumers' behavior) and conformity (penalty for people behaving different from the norm), where social interactions are directly embedded into the utility function via social utility. Our results succinctly clarify (1) how a positive spillover generally increases product demand (and the associated derived demand for labor), (2) how conformity pivots product demand around the expected market demand to make consumers less price responsive (and the associated derived demand for labor also less elastic), and (3) how social interactions in one good indirectly influence other goods' demands and the associated derived demand for labor.

3.1 Organizing Model

We begin with the total utility function (Brock and Durlauf 2001)

$$V(x, y; \alpha, \mu_x) = V(u(x, y), S(x; \mu_x, \alpha)) \quad (3.1)$$

$$\text{st. } p_x x + p_y y = M \quad (3.2)$$

where x and y are actions/choices made by an individual with the corresponding prices p_x and p_y , and $u(x, y)$ is the private utility associated with a choice bundle (x, y) . Here μ_x is the conditional probability measure of choices that a person places on the choices of others in the reference group, $S(x; \mu_x, \alpha)$ is social utility from the choice of the individual and his or her expectation of the choices of others, α is the parameter indicating the importance of social utility in total utility, and M is total resources.¹ Finally, we also assume a positive sign for $V_u > 0$, and that V_s has an uncertain sign depending on the form of interactions.

We consider two forms of social interactions: positive spillover and conformity. Positive spillover implies $V_s > 0$ (from social capital, neighborhood/peer, contagion, or conspicuous consumption effects). Conformity is associated with a negative contribution to utility because there is a disutility for being different, $V_s < 0$ (from class identity, social norm, relative income, or reference utility effects). Negative spillover can happen too via $V_s < 0$, or non-conformity by taking $V_s > 0$.

Because spillover is an externality relative to reference group behavior, forms like $S^{s1}(x; \mu_x, \alpha) = \alpha\mu_x x$, $S^{s2}(x; \mu_x, \alpha) = \alpha\mu_x x^2$, and $S^{s3}(x; \mu_x, \alpha) = \alpha\mu_x \sqrt{x}$ are examples of a spillover effect, where S_{xx} affects the slope of demand differently. The first spillover example above describes social capital or neighborhood effects. The second describes mathematically peer effects or contagion/herding. The third equation above represents conspicuous consumption or rat race spillover effects.

Conformity is a fundamental building block in social psychology. The idea is that individuals tend to conform to broadly defined social norms, with a magnitude depending on the cohesiveness, group size, and social support. One can model conformity as

$S^c(x; \mu_x, \alpha) = 1/|x - \mu_x|$ where someone is rewarded for behaving according to the norm. The form of social utility in S^c is difficult to work with analytically, and we need at least a restriction that $x \neq \mu_x$. Without loss of generality, we consider conformity a quadratic loss of utility such as $-S^{c1}(x; \mu_x, \alpha) = -\frac{\alpha}{2}(x - \mu_x)^2$, $-S^{c2}(x; \mu_x, \alpha) = -\frac{\alpha}{12}(x - \mu_x)^4$, or one such as $-S^{c3}(x; \mu_x, \alpha) = -\frac{\alpha}{4}(x^2 - \mu_x^2)^2$. The first representation of conformity captures social norm effects. The second is how reference income or utility effects look algebraically. The third type of conformity example above reflects threshold effects or demand maxima. Again, depending on the form of conformity via S_{xx} the effect of interactions on the demands for x and y may differ non-trivially.

3.2 Demand for the Good with Interactions, x

Interactions here are via the expectation of the demand for good x by a particular consumer, μ_x . In an ideal setting or small community an agent may observe others' demands for x and make sensible inferences concerning expected demand via the sample mean, median, or mode. In cases where the market is large the individual finds it harder to infer others' behavior and may resort to using existing norms.

To clarify the effect of interactions now we consider an exogenous change in μ_x and take the total differential of $S(x; \mu_x, \alpha)$, which is

$$dS = S_{xx}dx + S_{x\mu_x}d\mu_x + S_{x\alpha}d\alpha \quad (3.3)$$

The difference between the non-interactions case and any case with interdependence is through S_{xx} , $S_{x\mu_x}$, and $S_{x\alpha}$.

The effects of variables influencing demand here are

$$\text{change in price: } \frac{dx}{dp_x} = \frac{\overbrace{-\lambda p_y^2}^{\text{substitution effect part}} \overbrace{-x(p_y V_u u_{xy} + p_x V_u u_{yy})}^{\text{income effect part}}}{2p_x p_y V_u u_{xy} - p_x^2 V_u u_{yy} - p_y^2 V_u u_{xx} + (-p_y^2 V_S S_{xx})} \quad (3.4a)$$

$$\text{change in magnitude of interactions: } \frac{dx}{d\alpha} = \frac{p_y^2 V_S S_{x\alpha}}{\det H} \quad (3.4b)$$

$$\text{change in average market demand: } \frac{dx}{d\mu_x} = \frac{p_y^2 V_S S_{x\mu_x}}{\det H} \quad (3.4c)$$

where the matrix H is the Hessian, and the determinant of H is

$$\det H = 2p_x p_y V_u u_{xy} - p_x^2 V_u u_{yy} - p_y^2 V_u u_{xx} + (-p_y^2 V_S S_{xx}) > 0. \quad (3.5)$$

If the function $u(\bullet)$ is concave and $V(\bullet)$ is without interactions, the concavity of $u(\bullet)$ guarantees $\det H > 0$. However, with interactions present we still need to determine the sign of $p_y^2 V_S S_{xx}$ to decompose the effect of price on demand for x into income and substitution effects. Note that both components from the Slutsky equation are affected because interactions enter the denominator through $(-p_y^2 V_S S_{xx})$; it is true for all further cases below.

Figure 3.1 shows how exogenous positive spillover affects the demand for good x . All forms of spillover cause demand to increase because $S_{x\alpha}, S_{x\mu_x} > 0$. As a consequence, the associated derived demand for labor also increases. However, the functional form for social interactions has a profound effect on how exactly demand shifts. For S^{s1} (social capital) the shift is parallel, for S^{s2} (contagion) the effect is larger for higher levels of x , and for S^{s3} (conspicuous consumption) the effect is smaller for higher levels of x . Not only the level of shift differs but also the slope changes non-trivially. Because $S_{xx}^{s1} = 0$, $S_{xx}^{s2} > 0$, $S_{xx}^{s3} < 0$ the first demand curve has the same slope as the no interactions case, the second demand curve is the same shape but has steeper slope, and the third demand curve has a different shape than the no-

interactions case. The effect of an increase in average demand, μ_x , is qualitatively the same as a change importance of social interactions, α .

Although qualitatively all spillover effects have the same impact on demand, quantitative implications are dramatically different. Each new demand curve has a different elasticity, and potential policy implications can vary greatly. For example, when a researcher needs to calculate deadweight loss of fiscal policy such as taxation, the results differ for various demand curves. For spillover 1 the deadweight loss is the same as for the no interactions case. For spillover 2, the deadweight loss would be higher, and for spillover 3 the deadweight loss would lower than the baseline case of no interactions.

The effect of conformity in the utility function is summarized by Figure 3.2. For all forms of interactions the demand curve pivots around the point where $x = \mu_x$ because at that level of x we have $S_{x\alpha} = 0$. Although demand pivots around the average demand, μ_x , the slope of the new demand can be (1) uniformly flatter (S^{c1}), (2) become flatter as x changes (S^{c2}), or (3) the slope can change from flatter to steeper (S^{c3}). The effect of increase in average demand, μ_h , is also not uniform though all demand curves increase.

The intuition for conformity is that because there is a penalty for being different from the norm, there is a natural tendency for consumers to behave similarly. Therefore, the product demand curve is less elastic, and via Marshall's Fourth Rule so is the associated derived demand for labor less elastic. However, non-linearity of the conformity effect creates break-even points where consumers change behavior from being less responsive to the change in price to more sensitive to price changes. Some of the behavior resembles the Loss Aversion hypothesis.

The analysis not only stresses the need for modeling non-linear social interactions, but also underlines the fact that modeling interdependence by the theoretical setup in (3.1) and (3.2) is flexible and accommodates many realistic cases.

3.3 Demand for the Good without Interactions, y

We also analyze how interactions present in good x affect second good that does not have interactions, y . Comparative statics results are the derivatives:

$$\text{change in price: } \frac{dy}{dp_y} = \frac{\overbrace{-\lambda p_x^2}^{\text{substitution effect part}} \quad \overbrace{-y(p_x V_u u_{xy} - p_y V_u u_{xx} + (-p_y V_S S_{xx}))}^{\text{income effect part}}}{2p_x p_y V_u u_{xy} - p_x^2 V_u u_{yy} - p_y^2 V_u u_{xx} + (-p_y^2 V_S S_{xx})} \quad (3.6a)$$

$$\text{change in magnitude of interactions: } \frac{dy}{d\alpha} = \frac{-p_x p_y V_S S_{x\alpha}}{\det H} \quad (3.6b)$$

$$\text{change in average market demand: } \frac{dy}{d\mu_h} = \frac{-p_x p_y V_S S_{x\mu_x}}{\det H} \quad (3.6c)$$

Interactions affect every derivative through the denominator but interdependence also influences the income effect through $(-p_y V_S S_{xx})$. Because the budget constraint binds, any change in good x due to a change in the price of good y changes income for good y .

With a positive spillover effect in good x the demand for good y declines for all forms of spillover. An increase in average demand increases demand for y , even though the change differs by form of spillover. The slope can only be established for S^{s1} (social capital) as it is the same as the baseline case and demand declines uniformly (because $S_{xx}^{s1} = 0$ the slope for x did not change either). The other cases of spillover for which $S_{xx} \neq 0$ have uncertain change in the slope because $(-p_y^2 V_S S_{xx})$ in (3,6a) has both flattening and steepening effects.

In the case of conformity, it is unclear what happens to the demand for y because S_{xx} affects both the nominator and denominator of (3.6a). Even if we focus on the simplest case, S^{cl} , $S_{xx} = x - \mu_x$, and $dy/d\alpha = -p_x p_y V_S S_{xx} / \det H$ is uncertain a priori. Conditional on the level of x , for individuals with $x > \mu_h$ the demand for y is higher.³ For $x < \mu_h$ the demand for y is lower because more x is consumed, $dx/d\alpha > 0$. We still cannot determine how demand for y changes on the entire range of x because there is no reference point like μ_x in demand for the non-interactions good, y .

A graphical illustration can help. Think of an extreme case where demand for x becomes perfectly inelastic due to conformity, then demand for y becomes M_x / p_y , where $M_x = M - p_x \mu_x$ and μ_x represents a constant demand for x . Depending on whether x and y are complements or substitutes the change to the demand for y differs.

The effect of interactions in good x on the demand for good y appears in Figure 3.2. If without social interactions goods x and y are substitutes, $dx/dp_y > 0$, extreme conformity in x makes demand for good y is less elastic. With the presence of the substitute the demand for y was more elastic because consumers demand more of x to substitute because of the higher price of y . When the demand for x is fixed consumers cannot substitute y with x .

If without interdependence goods x and y are complements, $dx/dp_y < 0$, and the demand for good y with extreme conformity in x becomes more elastic relative to the case of no interactions. When there were no social interactions in x , both x and y were relatively tightly connected by being complements. When x is fixed and a certain part of income is spent on good y , the demand for y becomes more elastic.

Thus, how interactions in good x affect demand for good y and the demand for labor producing good y depends on the relationship between the two goods. In some cases we can make an inference, but the analysis becomes more involved, and the results may be less useful and intuitive. Nevertheless, we show how interactions in only one good affect the behavior of other goods as long as the goods are in the same consumer expenditure bundle.

3.4 Summary

In general, a positive spillover effect increases product and labor demand, and specific functional forms for social utility make the slope of demand change non-trivially. Demand can become more elastic over certain ranges of prices but less elastic over another ranges of prices. The magnitude of interactions is important because in some cases part of the population (say, low-demand consumers) may be more strongly affected by the interactions than the rest of consumers. With conformity, product demand pivots around the expected market demand, and product (and labor) demand becomes less elastic. A specific functional form can exaggerate or diminish the general changes to product demand and the associated demand for labor producing the good with attendant changes in the policy implications of, say a minimum wage, compared to the no-interactions case.

We also show that interactions in one good indirectly affect the demand for a good that has no direct interactions. The inter-good effect hinges on whether the two goods are complements or substitutes. We cannot analytically provide answers concerning how the non-interactions good (and associated demand for labor) is affected by an interactions type good without some prior knowledge of the relationship between the two commodities.

We acknowledge that there are other forms of interactions potentially represented by the social utility term $S(\bullet)$ besides spillover and conformity; the analytical representations may

vary, and interactions may operate through different channels such as via the budget constraint. However, we believe that spillover and conformity exhaust most of the real-life interactions problems and the examples demonstrate the flexibility of our model setup. Our results are useful for policy changes and welfare analysis. The qualitative effects on demand are relatively clear; the quantitative outcomes may have profound consequences on the correct measurement of the deadweight loss, behavioral effects of taxation, minimum wages, or jobs creation programs as the derived demand for labor mimics the product demand differences due to social interactions.

Additional Reading

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4. General Equilibrium and Welfare with Interdependent Preferences

The traditional trade-off discussed in economics is between equity and efficiency. The market may help best allocate resources but also generates inequality of incomes. The notion of equity-efficiency trade-off implicitly assumes that higher equality of incomes improves welfare. The government may in turn seek to affect total income inequality through lowering wealth inequality (as opposed to reducing earnings inequality), because it does not directly affect incentives to invest in human capital. Here we provide another argument why one needs to be careful in providing greater wealth equality when there are social interactions present. We do not claim that the situation here is the most general case but instead simply show that under asymmetric positive (altruism) or negative (envy) social interactions there are cases where some wealth inequality can be consistent with higher social welfare (Grodner and Kniesner 2008c).

The non-optimality of exactly equal incomes has been shown in the context of different risk aversion (Pestieau et al. 2002), uncertain incomes (Kreider 2003), and subjective levels of welfare (Alesina and La Ferrara, 2001). Further, in certain circumstances identical households may not necessarily be treated equally at the social welfare optimum (Mirrlees 1972, White 1981). The intuition behind the unequal treatment result is that there may be different resource costs of making various households equally well off. We extend the literature on evaluation of economic inequality by introducing social interactions, which have been shown to affect social welfare (Bernheim and Stark 1988, Kooreman and Schoonbeek 2004) and provide explanation for a greater concentration of wealth than labor earnings (De Nardi 2004).

We model heterogeneous agents in terms of wage distribution and introduce asymmetric social interactions where only one individual is either altruistic or envious. For simplicity, we use a quasi-linear utility function and assume an economy with two workers and two goods (leisure

and consumption). The results suggest that when workers have different wages it is optimal to redistribute wealth from high-wage workers to low-wage workers. In the case where workers have the same wages but one individual is social, the optimal wealth distribution suggests taking wealth away from the individual who derives more utility from wealth when given the same resources (with negative social interactions -- from the non-social individual; with positive social interactions -- from the social individual). However, when low-wage individuals are altruistic or high-wage individuals are envious, there are cases where it may be welfare-improving to increase wealth inequality by redistributing wealth from low-wage (low-earnings) individuals to high-wage (high-earnings) individuals. Once again we are not arguing that government policy to increase wealth inequality in general social welfare improving but rather use the situation to demonstrate how one must reason through policy affecting social welfare when social interactions are present.

4.1 Organizing Model

We begin with a two-worker, two-good economy where each worker has the same individual preferences for consumption and leisure. Heterogeneity of agents comes in via differences in wages. Social interactions are introduced to only one individual's preferences similarly to the approach in Brock and Durlauf (2001), where in addition to his or her individual utility the worker has a social portion in total utility. Social utility represents the fact that one cares for the other person's leisure. The simple setup allows for group distinctions such as selfish young vs. altruistic old or envious rich vs. altruistic poor.

Our approach from Grodner and Kniesner (2008b) is different from the standard general equilibrium framework where the social planner maximizes social welfare by choosing particular combinations of consumption and leisure for each individual, and where wealth is treated as an

exogenous endowment. In the following setup the social planner redistributes total wealth (Y) between two workers to maximize social welfare (W) subject to the population wealth constraint, where each worker individually maximizes utility subject to the individual budget constraint. The approach has been used in Moreno-Tenero and Roemer (2006).

Formally, the model can be represented as

$$\max_{Y_1, Y_2} W = W\left(V_1(c_1^*, l_1^*; \beta, S(l_2^*; \delta)), V_2(c_2^*, l_2^*; \beta)\right) \quad (4.1)$$

$$\text{st. } Y = Y_1 + Y_2 \quad \text{population wealth constraint,} \quad (4.2)$$

where subscripts index the worker, c is consumption of the generic good, l is leisure, $(\cdot)^*$ indicates the utility-maximizing choice for each individual of consumption and leisure, Y is wealth, S is social utility (which represents social interactions), V stands for total individual utility, W is the social welfare function (SWF), and β, δ are parameters. The social planner chooses a combination of wealth (Y_1, Y_2) that maximizes social welfare (4.1) subject to the individual maximization conditions and the population wealth constraint (4.2).

The social maximization condition requires that the social welfare function (SWF) marginal rate of substitution equals minus the slope of the utility possibility frontier

$$W_{V_1} / W_{V_2} = -dV_1 / dV_2, \quad (4.3)$$

where W_{V_1} and W_{V_2} represent marginal social utilities with respect to individual utilities. Because the distribution is done with respect to wealth, there is no clear relation of the ratio in (4.3) to a particular wealth distribution. Therefore we want to restate the condition in wealth space as

$$W_{Y_1} / W_{Y_2} = -dY_1 / dY_2 = 1 \quad (4.4)$$

because the budget constraint is a straight line with the slope of negative one. By representing the SWF as an indirect social welfare function in w and Y , and considering that condition (4.3) must be satisfied for the solution of the optimization problem (4.4) given $(w_1, w_2, \beta, \delta)$, we have

$$\left(W_{V_1} \frac{\partial V_1(w_1, Y_1^{**})}{\partial Y_1} \right) / \left(W_{V_2} \frac{\partial V_2(w_2, Y_2^{**})}{\partial Y_2} + W_{V_1} \frac{\partial V_1}{\partial S} \frac{\partial S(w_2, Y_2^{**})}{\partial Y_2} \right) = 1. \quad (4.5)$$

where (Y_1^{**}, Y_2^{**}) is the wealth distribution at the social optimum. Notice that due to social interactions the marginal utility of wealth for the second individual is altered by

$W_{V_1} \frac{\partial V_1}{\partial S} \frac{\partial S(w_2, Y_2^{**})}{\partial Y_2}$ because the leisure of the second worker affects the first worker's utility.

Suppose there are no social interactions, then $W_{V_1} \frac{\partial V_1}{\partial S} \frac{\partial S(w_2, Y_2^{**})}{\partial Y_2} = 0$. For the social

optimum to be at an equal wealth distribution, that is $Y_1^{**} = Y_2^{**}$, either wages have to be the same ($w_1 = w_2$), or there is no income effect due to a change in wages ($dY_i / dw_i = 0$). Both assumptions are special cases so that wage heterogeneity should generally result in an unequal optimal distribution of wealth.

By the same token, when there are social interactions but wages are equal ($w_1 = w_2$), the optimum in (4.5) holds only when $\frac{\partial S(w_2, Y_2^{**})}{\partial Y_2} = 0$. The effect of income on social utility is zero

only when the second worker's demand for leisure is not affected by income (dl_2^* / dY_2), which again is a (very) special case.

So, in general, both wage dispersion and social interactions should produce unequal wealth distribution at the social optimum. Only when the effects exactly counteract each other is

there a possibility of an equal wealth distribution, which we again note needs to be regarded as a special case.

4.2 An Example of Asymmetric Social Interactions

We now demonstrate the implications of the model in a case with additive, equal weights in the Social Welfare Function and quasi-linear underlying individual utility functions. Here the social utility enters into preferences of one individual additively. Our choice of the utilitarian SWF is to make individuals be treated equally by the social planner and prefer equal distribution of utility (not wealth). Our choice of additive social interactions ensures that the model does not overemphasize the effect of interdependence on individual demands. The simple setup maximizes tractability of the model while maintaining the avenue for social interactions.

We define asymmetric interactions as when only one individual responds to the behavior of the other individual, such as in

$$u_1 = \beta_c \sqrt{c_1} + \beta_l \sqrt{l_1} + \delta_l \sqrt{l_2} \quad (4.6)$$

$$u_2 = \beta_c \sqrt{c_2} + \beta_l \sqrt{l_2}, \quad (4.7)$$

Where once again c is consumption of the generic good, l is leisure, T is total available time, w is the wage rate (price of consumption is 1 and is taken as the numeraire), Y is a non-labor income, and $\beta_c, \beta_l, \delta_l$ are parameters.¹² Note that $(T-l)$ represents labor supply and $w(T-l)$ is total earnings. The utility function in (4.6) and (4.7) has the property that even though it is quasi-

12. We use wealth and non-labor income as equivalent although in practice wealth is a sum of non-labor incomes discounted by the interest rate. For the purposes of tractability in presentation we ignore the distinction.

linear, the utility possibility frontier is still convex. Finally, each individual faces a similar budget constraint

$$c_i + w_i l_i = w_i T + Y_i, \quad i = 1, 2 \quad (4.8)$$

where i indexes the individual ($i = 1, 2$).

The parameter δ_i represents the effect of social interactions.¹³ When $\delta_i > 0$ we can think about the altruistic behavior of the first individual with respect to the second individual (a spouse cares for the partner's leisure or parents care for leisure of their offspring), but when $\delta_i < 0$ we can think about envious behavior (in the family setting, siblings compete over how much attention they are given by their parents because attention translates into higher levels of quality for leisure time).

The demands for both individuals are the same:

$$c_i = (w_i T + Y_i) P_{c_i} \quad (4.9)$$

$$l_i = (w_i T + Y_i) P_{l_i}, \quad (4.10)$$

where $P_{c_i} = 1 / (1 + \beta_i^2 / (\beta_c^2 w_i))$ and $P_{l_i} = 1 / (w_i (1 + (\beta_c^2 w_i) / \beta_i^2))$.

However, the indirect utility functions become

$$V_i = \sqrt{(w_i T + Y_i)} (\beta_c \sqrt{P_{c_i}} + \beta_l \sqrt{P_{l_i}}) + \delta_i \sqrt{(w_i T + Y_i) P_{l_i}} \quad \text{and} \quad (4.11)$$

13. A more general model would have δ_j being individual-specific or good-specific. In that framework we would choose particular parameters so that $\delta_{ji} \neq 0$, where j represents a good and i indexes an individual. Discussing interactions in only one good and in one other individual is sufficient to draw conclusions that reflect more general models.

$$V_2 = \sqrt{(w_2 T + Y_2)} (\beta_c \sqrt{P_{c_2}} + \beta_l \sqrt{P_{l_2}}). \quad (4.12)$$

The problem for the benevolent planner is to maximize the social welfare function subject to the population wealth constraint defined by wealth limits ($Y = Y_1 + Y_2$) and requirement for individuals to maximize their utility (4.11 and 4.12). The optimal allocation of wealth now becomes

$$Y_1 = ((Y + w_2 T) - P^2 w_1 T) / (P^2 + 1) \quad (4.13)$$

$$Y_2 = (P^2 (Y + w_1 T) - w_2 T) / (P^2 + 1) \quad (4.14)$$

where $P = (\beta_c \sqrt{P_{c_2}} + (\beta_l + \delta_l) \sqrt{P_{l_2}}) / (\beta_c \sqrt{P_{c_1}} + \beta_l \sqrt{P_{l_1}})$.

4.3 Simulation Experiments

Similar to DeNardi (2004), who draws meaningful conclusions when examining the evolution of wealth in a model with bequests through simulation experiments, we discuss implications of our model by setting particular parameter values and performing numerical calculations. In what follows we do not prove that wealth inequality is generally desired, or find conditions for such a situation, or even try to match the U.S. economy's distributions of wealth, earnings, or total income. The goal of our research is to provide cases demonstrating the basic result that when social interactions are present it may be beneficial to redistribute wealth away from low-income individuals, even when it makes them poorer by any objective measure. Because we only attempt to prove the existence of this somewhat counter-intuitive result, it is enough to demonstrate several plausible cases.

Using the calibration presented in Grodner and Kniesner (2006) we choose $\beta_c = 0.0492$, $\beta_l = 0.0466$, and $\delta = 0,01$ (altruistic individual) or -0.01 (envious person). Wages range from 0.65 to 0.90 and the total wealth to be distributed equals 1466. In the discussion below we label

workers as [1] or [2] where the square brackets distinguish the labels for workers from those of equation numbers. Each table fixes the characteristics for worker [2] and changes either the wage or intensity of social interactions for worker [1], which are presented in the far left column. The numbers inside the tables are ratios of incomes or utilities for worker [1] versus worker [2]. Income stands for total income and equals wealth plus earnings, which are measured by wage times hours worked. For comparison, the results on the left in each table are for an equal distribution of wealth, and results on the right represent optimal distributions of wealth, which maximize social welfare.

4.3.1 Wage Heterogeneity

Starting at equality, as the wage for individual [1] increases the social planner needs to take away wealth from the high-wage worker [1] and distribute it to the low-wage worker [2]. It can be seen in equations (4.13) and (4.14), when we set $P = 1$ (no social interactions). The intuition is that the marginal utility of wealth for the low-wage worker [2] is higher than the marginal utility of wealth for the high-wage worker [1]. It is then beneficial to transfer wealth to the person whose utility experiences the greater gain due to the transfer. However, there is still equality of total income because the high-wage individual [1] makes up for lower levels of wealth by having higher earnings. The result recasts the long-standing equity-efficiency tradeoff whereby an increase in the inequality of wealth or income creates less inefficiency in the ultimate utility (efficient) outcome.

4.3.2 Social Interactions

Now consider social interactions when wages are initially equal. The optimal distribution of wealth has the altruistic ($\delta > 0$ and $P > 1$) individual [1] receiving less wealth. The result can be seen in equation (4.11) where the social individual [1] derives positive utility from wealth of

the non-social individual [2] and needs to make up for the difference with higher earnings. Again, the social planner needs to transfer wealth to the non-social individual [2] for whom the marginal utility of wealth is higher to increase total welfare. However, notice that in all cases the social individual has more utility and by objectives measures it is hard to tell who is better off.

The results can also be seen from studying equations (4.13) and (4.14). When there are no social interactions, $P = 1$ and the solution is symmetric. When the social individual is altruistic $\delta > 0$, we have $P > 1$, and thus $P^2 > 1$. Then there are two effects why the non-social individual needs to have more wealth: $Y_2 > Y_1$ because (i) in the outcome equation for Y_2 , $P^2 Y > Y$, which is a pure wealth effect, and because (ii) $wT(P^2 - 1) > 0 > wT(1 - P^2)$, which is an earnings effect. When the social individual is envious $\delta < 0$, and we have $P < 1$ and $P^2 < 1$. Then there are two effects why the non-social individual needs to have less wealth: $Y_1 > Y_2$ because (i) in the outcome equation for Y_2 , $P^2 Y < Y$, which is a pure wealth effect, and because (ii) $wT(P^2 - 1) < 0$, which is an earnings effect. We can also see it as a make up for a lower marginal utility of earnings of the social individual, which needs to be compensated with wealth, because in the outcome equation for Y_1 we have $wT(1 - P^2) > 0$. The earnings distribution is primarily determined by wages because even with social interactions the demands for consumption and leisure are the same (4.9 and 4.10).

4.3.3 Wage Heterogeneity Plus Social Interactions

So far the individual from whom it was beneficial to transfer away wealth is no worse off either by having equal total income (in the case of wage heterogeneity) or by having higher earnings (in the case of social interactions). Now we turn to the case where an individual can be worse off in both objective measures, and yet be better off in terms of welfare.

Table 4.1 presents the case of an altruistic individual [1] who has low wages (below 0.8702, which is the wage for the high-wage worker [2]). Notice that for wages below 0.75 the low-wage worker [1] has more wealth because the wage heterogeneity effect (transfer wealth to [1]) dominates the social interactions effect (transfer wealth from [1]). However, in the range of wages 0.77–0.8702 the low-wage, altruistic worker [1] has both lower wealth and lower earnings but yet higher utility. Table 4.2 likewise demonstrates a similar case with a high-wage, non-social worker having more wealth and earnings and yet lower utility.

4.3.4 Summary

For the purposes of demonstrating how policy exercises change when there are social interactions we have demonstrated a case where in the presence of a small amount of wage inequality it may be welfare improving to transfer wealth away from altruistic, low-wage workers towards non-social high-wage workers. By objective measures of economic equality (wealth, earnings) one individual is worse off, and yet that worker is better off in terms of utility level. The intuition is that with social interactions the efficiency-equity tradeoff no longer determines the effect of transfers on well-being. Our simulations underscore the importance of incorporating social interactions when studying the policies affecting the distributions of wealth and earnings.

4.4 Wealth Distribution Policy Implications

We have presented a model with two heterogeneous individuals deriving utility from consumption and leisure where one of them receives utility from the other's leisure (asymmetric interactions). The presence of a high level of wage dispersion suggests a higher wealth inequality and also higher earnings inequality at the social optimum, so that both distributions have compensating effects that result in equality of total income. When there is interdependence,

inequality of wealth may not be undesirable because it reduces inequality of utility. When there is both wage inequality and utility interdependence then there is a possibility of wealth equality as well as any form of wealth inequality -- it depends on the inter-play of the wage heterogeneity and social interactions effects.

The results of our numerical simulations demonstrate that under limited wage inequality it may be beneficial for society to transfer wealth away from altruistic, low-wage workers. The economically regressive transfer is social welfare improving even though by the objective measures of economic well-being (wealth or earnings) the low-wage individual has less resources, while the other individual is worse off in terms of utility. This underlines the importance of considering social interactions when studying the policies affecting distribution of income.

We do not argue that the results of our simulations imply that wealth inequality is always beneficial for a society with unequal wages and social interactions. Rather, we point out the possibility of wealth and income inequalities that maximize social welfare because social interactions in utility can potentially mitigate the adverse effects of economic inequality. In some circumstances optimal inequality creates an outcome that is desirable from a social welfare perspective because it reduces inequality of utility. In the presence of social interactions the redistribution should be from high-utility individuals to low-utility individuals. A just society may be willing to perform such a redistribution and also regard it as fair. For any sensible policy, though, it will be critical to identify correctly the high-utility individuals, who may either be social or non-social, and that will be a formidable task.

Additional Reading

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5. Empirical Welfare Analysis: Social Interactions and Poverty Spell Length

Our research in the following section examines how individual and community factors influence the average length of poverty spells, which are the number of months with income below a U.S. federal government poverty income threshold. We measure local economic conditions by the county unemployment rate and neighborhood spillover effects by the racial makeup and poverty rate of the county. We find that moving an individual from one standard deviation above the mean poverty rate to one standard deviation below the mean poverty rate (from the inner city to the suburbs) lowers the average poverty spell by 20–25 percent; this is equal in magnitude to the effect of changing the household head from female to male. Finally, we find that when we control for the demographic, human capital, and county level effects the conditional effect for high school graduates is only two months (85 percent smaller than the unconditional effect), black poverty spells are about eight months (half of the unconditional effect), and female headed households increase length of spells by about eight months (80 percent of the unconditional effect).

5.1 Overview

Although the U.S. has experienced an unprecedented GDP growth over the past 50 years, there still has been a double-digit poverty rate partially due to an uneven distribution of prosperity (Hoynes, Page, and Stevens 2006, Danziger and Danziger 2006). Part of the problem includes neighborhood specific factors that increasingly play a prominent role in both economic research in general (Brock and Durlauf 2000, Manski 2000) and in poverty research in particular (Small and Stark, Luchter, Qian, and Crowley, Hannon in the Special Issue on "Income, Poverty, and Opportunity," (2005) *Social Science Quarterly* 86(s1)). There is strong evidence that individual outcomes are related to local crime rates (Glaeser, Sacerdote and Scheinkman 1996),

educational segregation and peers (Clapp and Ross 2004), human capital spillover in local labor markets (Glaeser 2000), or racial composition of neighborhoods (Quillian 2003). One of the classic examples is the follow-up study to the Gautreaux experiment, which provides strong evidence for possible link between better neighborhood quality characteristics and higher family incomes (Keels et al 2005). Given the importance of neighborhood effects and their strong relevance for the study of individual poverty, we have used unique individual data matched with county level statistics to study the effects of county level unemployment, racial composition, and poverty rates on the length of time individuals spend being poor.

In our research we ask how individual and community factors influence the average length of poverty spells (Grodner, Bishop, and Kniesner 2010). We use the term community factors to describe two distinct phenomena: local economic conditions and social interactions. The concern over local economic conditions is easily motivated: is the persistence of poverty greater in counties with high rates of unemployment? To introduce the notion of social interactions we follow Durlauf (2003) who argues that individuals are influenced by neighborhood spillover effects. For example, persons in counties with chronically high poverty rates may suffer greater poverty persistence even when controlling for local economic conditions because of peer pressure or norms. Similarly, counties with high proportions of minority residents may have lower levels of social capital and hence longer spells of poverty.

We address four potential explanations for the behavior of individuals in poverty. Demographic characteristics are expressed by race, gender, and marital status. Human capital explanations are captured by the education and age of the household head. Local market conditions are represented by the level of unemployment in a county. Finally, social interaction effects are captured by the percent black and percent poor in a county. To study the

demographic, human capital and county level effects on the average poverty spell length we use a matched PSID/Census sample.

The data we discuss here cover 1968–1989 and include annual poverty spells (greater than 12 months). The average poverty spell is nearly 39 months. The average black poverty spell length is 16 months longer than the average white poverty spell. The average female headed household poverty spell is 9.3 months longer than that of male headed households. High school graduate households suffer 12 fewer months of poverty than dropout households. However, when we control for the demographic, human capital, and county level effects we find that the relative high school graduate poverty spell falls by 85 percent (2 months), the black poverty spell falls by half (7.8 months), and the female headed household's poverty spell falls by 20 percent (7.7 months). Consistent with a life cycle explanation, we find that for both races the poverty spell length first falls in childhood, rises in adulthood, and then falls again after retirement. By using separate equations for whites and blacks we find important differences in the factors (other than age) that influence poverty spells across races.

We consider the effect of a county's unemployment rate, poverty rate and racial makeup on the length of a poverty spell too. Of the three area factors, the percentage of poor in a county has the largest effect. Moving an individual from one standard deviation below the mean poverty rate to one standard deviation above the mean poverty rate (from the inner city to the suburbs) may lower the average poverty spell length by 20 to 25 percent. The area poverty rate effect just mentioned is equal in magnitude to changing the household head from female to male.

The results of our research to follow are mainly descriptive, and we do not claim to have identified causality between all the independent variables and the poverty measures. However,

the effects of the demographic, human capital, county level characteristics are sensible, and both statistically and economically significant.

5.2 Some Background Literature

Stephen Jenkins (2000) in his Presidential Address to the European Society for Population Economics observes that much more is known about long-run trends in poverty than about the short-run dynamics of poverty (p.530). For example, a large body of research identifies the demographic and human capital characteristics of the poor (Danziger and Haveman, 2001). The literature on poverty persistence is not nearly as large.

The seminal paper investigating the dynamics of poverty using spell duration and exit probabilities is Bane and Ellwood (1986). Using 12 years of data (1970–1982) from the Panel Study of Income Dynamics (PSID) Bane and Ellwood find that most persons who become poor have only a short stay in poverty. At any given time the majority of the people who are poor are in the midst of a long spell of poverty, though.

More recently, Stevens (1999) advances the study of poverty dynamics by estimating the time spent in poverty over multiple spells. Like Bane and Ellwood, she finds substantial persistence among the stock of poor individuals. In contrast to Bane and Ellwood, she finds substantial persistence among the persons who flow into poverty. Stevens notes that single spell analyses find that most people will be poor for less than two years (Gottschalk et al., 1994); her multiple spell analysis highlights that the average time in poverty over a decade is four years.

Jenkins noted that much of the poverty dynamics literature (following Bane and Ellwood) focuses on consecutive observations within a given state or poverty spell. He further noted a need to study the “longitudinal *patterns* of poverty experience” (p.535). The original contribution to the study of poverty patterns is the well-known *Years of Poverty, Years of Plenty* (Duncan et

al., 1984). A more thorough review of the empirical literature concerning poverty transitions appears in McKernan and Ratcliffe (2005).

The effects of the neighborhood characteristics on the situation of the poor also have gained considerable attention. Specifically, Quillian (2003) uses the PSID to provide evidence that blacks stay longer in poor neighborhoods, and Keels et al. (2005) report success of poor black households who were relocated to more affluent suburban neighborhoods from downtown Chicago as a result of the Gautreaux residential mobility program.

5.3 Methods and Data

The contribution of our research is in the inclusion of the local market and social interaction effects. To study the characteristics that describe the length of a poverty spell we choose a linear regression approach. The strategy has an advantage of a simple interpretation and easy introduction of non-linearity. Our model is

$$\text{Poverty spell length (months)} = f(D, H, C), \quad (5.1)$$

where D is demographic characteristics including race and gender, H includes human capital factors such as the household head's education and age as well as the individual's age (cubic), and C includes county level variables such as percent unemployed, percent black, and county poverty rate, all of which are quadratic (Grodner, Bishop, and Kniesner 2010).

The approach of using Ordinary Least Squares (OLS) is a major simplification that ignores spell dependence, non-normal distribution of the error term, spell censoring, and non-linearity of the spell length. It is well documented that the conditional probability of exiting poverty during a particular year, given the number of years a person has been poor, a hazard rate, is non-negligible (Bane and Ellwood 1986, Stevens 1999). The violation of the assumed ex ante distribution on the error term complicates informative inference on the distributional shape of

outcomes. The censoring can create a significant bias to the estimates for the same reasons that the bias is present in all limited dependent variable models. Because of spell dependence the relationship between independent variables and the duration is always non-linear, with the simplest possibility being the log duration model.

Equation (5.1) could potentially be estimated by duration model methods. However, the disadvantages of the typical duration model are the often strong parametric assumptions on the hazard rate and a non-trivial computation of the marginal effects on the length of the spell. In some models it may be difficult to obtain standard errors for the marginal effects. Moreover, the solutions to the left censoring may have a large effect on the predicted spell length because of the usually assumed extreme value distribution on the error term (it may predict overly long spell lengths, which in turn distorts the predicted mean duration). In general, the marginal effects of independent variables on the spell length in duration models may vary greatly between various specifications, which is mainly due to the fact that the duration model is not designed to compute marginal effects in the first place and one need do multiple transformations to calculate them.

We believe that the benefits of using simple linear regression outweigh the disadvantages in our application. Multivariate regression overcomes the difficulty of computing the marginal effects because they come directly from the parameter values in OLS. We can easily capture non-linearity in the relationship between spell length and independent variables by including both polynomial and interactions terms. Depending on the level of censoring it is possible that if the bias to OLS is small, the estimates may actually be more robust and close to the true values than marginal effects computed from different specifications of the duration models. In contrast to the duration models, consistency of the OLS does not require assumption of any particular distribution on the errors as long as the expected value of the innovations is zero. Still, the

standard errors may be incorrect in OLS, but we may induce more bias by computing non-linear functions of the standard errors for marginal effects from potentially mis-specified parametric duration models.

Another issue is the potential self-selection of poor individuals into the counties with high percentage poor. It may be particularly important if persons who, on average, have short spells of poverty locate themselves in counties with small numbers of poor persons. We may then observe a positive relationship between poverty rate and the length of the poverty spell but not due to a casual effect, but rather due to self-selection. Because the PSID follows individuals we have records of their movements between counties, and we can partially mitigate the effect of self-selection by controlling with dummy variables for movers. We did not attempt a Heckman's self-selection model because we could not determine variables that affect selection of individuals into the high poverty counties but do not also affect poverty spell length (an exclusion restriction), and because the movers are relatively a small part of the sample, just over 15%. (Self-selection should affect in similar ways OLS and duration model estimates, however, the problem is easier to solve in OLS because of the well-established set of econometric techniques in light of the information in the data.)

A linear regression with multiple non-linear terms may then be better suited for our purpose of estimating the marginal effects. Obviously, estimating the true duration model is the appropriate method for poverty spell length modeling and computing marginal effects. It is possible that a mis-specified duration model is more severely biased than the OLS. In any event, we present competing duration method results and argue that they are inferior to our OLS estimates.

5.3.1 Data Sources

Our primary data source is the Panel Study of Income Dynamics (PSID) for 1968–1989 (Stevens 1999). We study only persons who were poor at least once during the sample period. Following Stevens, we take a broadened definition of poverty as having a family income that is below 125 percent of the U.S. federal government’s official poverty line income for the structure family in question. We ignore all individuals who have never been poor assuming that they are very different from people who have ever been poor.

In addition to the rich selection of individual and family characteristics, we use information about county location for each person. We matched county level data (poverty rates, racial makeup) from the 1970, 1980, and 1990 Censuses. The data points for years in between censuses were obtained by imputing information by the closest census data and then adjusting the weighted average to the national mean as reported by the *Statistical Abstract of the United States*.

Annual county level unemployment rates are available from 1975 onward. The years for which unemployment data were not available include information from the closest year available. All weighted averages were corrected to match the annual mean as reported in the *Statistical Abstract of the United States*.

All county-level variables for each spell are for the beginning of the spell. We may be ignoring potentially useful within-spell information about changes in the county characteristics. At the same time, any measure of the central tendency (mean, median, mode) will be affected by the mobility decisions of persons who change counties, and so will not be exogenous to the length of the poverty spell. A potential regressor candidate would be the difference in the value of each county's characteristic in the first and the last period of the poverty spell. Again, we

would have to separate trends in county characteristics from the national trends (say, take into account the increase in the poverty during the 1970s). We believe that using the first period's characteristics gives us a good way to benchmark each individual's county characteristics, especially because we can condition the estimated effects by using a full set of year dummy variables.

5.3.2 Summary Statistics

We focus on the distinction between individuals in poverty, spells of poverty, and years in poverty (per individual or per spell). The idea can be most easily demonstrated by the following schematic:

														TOT
Year	68	69	70	71	72	73	74	75	76	77	78	79	80	13
Poor=1	0	0	1	1	1	1	0	0	0	1	1	1	0	7
Person	<----- years in sample ----->												1	
Spell	<---- spell ---->						<- spell ->						2	
Spell-year	◇ ◇ ◇ ◇									◇ ◇ ◇			7	

During the 13 years shown in the above example, there are two spells of poverty, one of three poverty years, and one of four poverty years, for a total of seven poverty years. The average number of years per spell for a particular person is 3.5 years. Previous studies of poverty dynamics studies do not make a distinction between single and multiple poverty spells by the same person. Duration studies usually focus on individual spells only and do not examine the particular pattern of poverty transitions (the exception is Stevens 1999).

The importance of identifying the patterns of poverty can be illustrated by the following example. Suppose two individuals are in the sample during all 13 years and each is poor during seven of the years. The first person is poor during the first seven years, ends his poverty period, and stays non-poor for the rest of the time frame. In contrast, suppose the second person alternates between states of poverty and non-poverty during the same time frame. Clearly, policies designed to aid the first person who suffers prolonged periods of poverty may not be effective in helping the second person who suffers multiple, but short periods of poverty.

Table 5.1 provides some summary statistics used in our examination of the length of poverty spells. Our sample contains 27,020 poverty spells with an average spell length of about 39 months. About 54 percent of the people have a single poverty spell. We consider three types of variables, individual characteristics, head of household characteristics, and county characteristics. The individuals in our sample of poverty spells have an average age of 23 years, are nearly two-thirds black (64 percent), and slightly more likely to be female (54 percent). The household heads are 42 percent unmarried females, 52 percent married, and about seven percent unmarried males. Only slightly more than one-third of the household heads are high school graduates. More than 70 percent of the household heads are between 25 and 60 years of age. The typical county of residence by a poor individual has an unemployment rate of about 6 percent, is nearly one-quarter black, and has a poverty rate of over 16 percent.

Table 5.1 also provides summary statistics for average poverty spell length. Blacks on average are poor for about 44 months and whites for 29 months. Persons in female-headed households have poverty spells that are 9 months longer on average than persons living in male-headed households. Persons living in households where the head is a high school dropout suffer an additional 13 months of poverty.

5.4 Empirical Results

We divide our discussion based on Grodner, Bishop, and Kniesner (2010) into three sections. First, we note basic demographic influences on poverty spell length. Then we consider the effect of an individual's age on poverty spell length. Finally, we examine the effect of county characteristics on average poverty spell length. We also provide estimates using alternative data sample selection criteria in order to gauge the sensitivity of our county level results.

5.4.1 Demographic Indicators

Table 5.1 also lists regression coefficients for the demographic indicator variables. The dependent variable is the number of months an individual spends in poverty. In addition to race we consider the relative effects of the household head's gender (female-head), education (high school), and the age (agehead_0-25 and agehead_60), as well as the gender of the individual (female). All regressions include state and year dummies plus indicator variables for persons who changed counties during poverty spell (movers). We include variables for the individual's own age and the county-level effects but report them in separate sections.

Each regression also contains dummy variables for left-censored and right-censored spells, which is equivalent to running a model with only uncensored spells, but is more efficient because it uses all observations. There is a possible bias in our estimates because the censoring dummies are an aspect of the dependent variable. However, because we have about the same number of left and right-censored spells we believe that the opposite effects of the censored spell dummy variables mostly cancel out. We later show that by using our simple regression results we have both significant gains in predictive power and the implied marginal effects are more stable than in traditional duration models (Table 5.2). In other words, we acknowledge that by design our model and the use of the dummies for censored spells can create a bias, but because

the purpose of our project is to predict the conditional poverty spell length, the OLS is our preferred model by virtue of being the most robust and stable estimation technique.¹⁴

The first column of Table 5.1 reports the demographic coefficients without the county level effects in the regression. Comparing the coefficients in column one with the coefficients with the county level effects (column 2) shows little difference in the coefficient values across model specifications. This allows us to concentrate on the regression results that include the county level effects.

Table 5.1, column 2 also reveals that being black, female, or living in a female headed household increase poverty spell length while living with a head with a high school education or who is than less than 25 years old reduces the average spell length. All of the above coefficients are significant at the one percent level. Furthermore, we find that living in a married household (relative to the omitted group, single male head) or living with a head greater than 60 years old (relative to a head between ages 25 and 59) does not significantly affect the length of the poverty spell.

Examining the magnitude of the effects of demographic indicator variables on poverty spell length, we find that blacks' suffer about eight more months of poverty than the typical individual in a white-headed household. Individuals living in female-headed households also suffer poverty spells that are about eight months longer than the omitted group's, unmarried male heads. Living in a family with a high-school educated head reduces poverty spells by approximately two months. Persons living with heads less than 26 years old have poverty spells

14. When using the PSID data too Stevens (1999) found that ignoring right-censored spells in a duration model did not affect any signs and statistical significance of the regression coefficients.

that are about five months shorter than those living with older heads. Individual female poverty spells are 1–2 months longer than male poverty spells.

It is useful to compare the predicted poverty spells from Table 5.1 with the observed poverty spells also noted in Table 5.1. The black/white observed gap is just under 16 months (44.46 – 28.70); however, the predicted gap is only about eight months. Thus, controlling for other factors reduces the black/white gap in half. For female heads the observed gap is just over nine months and the conditional gap is under eight months. Only about 20 percent of the female head's gap is explained by differences in the covariates. In contrast, high-school dropouts have an observed gap of almost 13 months while the conditional gap is under two months. Almost all (85 percent) of the gap between high school graduates and dropouts can be explained differences in the controlling factors.

Columns 3 and 4 of Table 5.1 present the regression results by race. It is quickly apparent that race matters so to speak. The difference between the races is most obvious for female heads and heads less than 26 years old. Individuals in black, female-headed households suffer over nine more months of poverty while individuals in white, female-headed households suffer only four more months of poverty. Living with a young head shortens the average black poverty spell by more than six months while living with a young head shortens poverty spells for whites by only under three months.

5.4.2 Individual's Age

We model an individual's age and the length of the poverty spell as a cubic function. Interpreting the meaning of a cubic function from a table is burdensome; we use simple plots together with 95 percent confidence bands to explore the relationship between age and poverty spell length.

Figures 5.1a and 5.1b present the conditional predicted poverty spell length by age for white versus black individuals. Figure 5.1a is the white age effect. The cubic function appears to fit the data quite well; poverty spell length declines as white children age and then begins to rise during adulthood. White individuals near retirement age have poverty spells of approximately the same length as small children. After retirement age white poverty spell length declines continuously.

We present the black age effect in Figure 5.1b. Unlike other demographic indicators such as female-head we find little difference in the age effect between races. We conclude that for both races poverty spell length falls in childhood, rises in adulthood and falls again after retirement, which seems to reflect reasonably the expected life cycle.

5.4.3 County Level Effects

Our primary interest is in investigating the relationship between poverty spell length and county level neighborhood effects. By modeling the poverty spell length as a function of a county's unemployment rate we can examine the impact of local market conditions on spell length. To capture the impact of social interactions we model poverty spell length as a function of the county's racial makeup (percent black). Further, we consider the effect of the percent poor in a county on the average poverty spell length, which we suspect contains elements of both local market conditions and social interactions. We present our results by race.

Figures 5.2a and 5.2b provide a useful picture of the influence of county poverty on the length of an individual's poverty spell. The county's percent poor has a positive and linear relationship with the poverty spell length for both whites and blacks. Not only do county characteristics appear to relate to the spell length of the poor non-linearly, but blacks and whites also differ in the type and intensity of the association.

At this point it is useful to ask what is the (relative) magnitude of the county level effects. One benchmark is comparing the effect of a head with a high school degree. In Table 5.1 we see that not having a high school degree adds approximately two months to a poverty spell in the both races sample. The percent unemployed for whites and the percent poor for blacks are the county level effects with the greatest magnitudes. Using our point estimates, more fully presented in Grodner, Bishop, and Kniesner (2010), we find that an increase in the county unemployment rate from 4.0 to 6.5 percent is associated with a two-month increase in poverty spells for whites. An increase in the percentage poor in a county from 10 to 13 percent is associated with a two-month increase in poverty spells for blacks.

We have just seen that relatively modest changes in the county level indicators have non-negligible level of association with the average length of the poverty spell. Suppose for the purpose of discussion that the effect is causal and we consider the change in the percent poor in a county from one standard deviation below the mean to one standard deviation above the mean (mean = 16.5, standard deviation = 7.9). If we move a white individual from a county that is 24 percent poor to one that is eight percent poor the average poverty spell falls by 20 percent (about six months). The same change for black individuals may result in an 11-month decrease (25 percent). In both cases the effect is greater than that of a female head on the average poverty spell. A similar experiment for whites and unemployment results in a four-month decrease in poverty, again similar in magnitude to the white female-head effect.

How realistic is this assumption of moving individuals from a county with a poverty rate of 24 percent to a county of eight percent? Consider the following examples of neighboring localities (Census estimates): District of Columbia (17 percent) and Fairfax County, VA (five percent); City of Richmond (20 percent) and Chesterfield County (six percent); Orleans Parish

(New Orleans, 27 percent) and St. Tammany Parish (Slidell, 11 percent); and rural Northampton County, NC (22 percent) and Wake County (Raleigh, eight percent). This implies that moving from one standard deviation above the mean poverty rate to one standard deviation below the poverty rate is equivalent to moving people from either the inner city to the suburbs or from the countryside to the city.

5.4.4 Sensitivity Checks

Finally, we confront here the possible issues of misspecification of OLS by running censored regression (censored from the right for spells still in progress) to control for censoring, censored regression on log of poverty months to control for a non-normal error term, and a more general Weibull model with and without right censoring to investigate the effect of a flexible functional form. A duration model assuming a Gamma distribution on the hazard rate did not converge, and we did not estimate proportional hazard models due to difficulty with obtaining marginal effects. We also ignored left censoring, unobserved heterogeneity, and multiple spells, which are relatively complicated issues.

Table 5.2 presents the results of our further robustness checks. The first column presents the OLS results from the full dataset with all people (as in Table 5.1). Controlling for right censoring (second column) does not change the signs or magnitudes of the estimated effects, and most coefficients are within two standard deviations of the OLS results. Using a dependent variable that is the log of poverty periods has little impact on our estimates as well. However, the use of a parametric Weibull model affects the coefficients substantially. For example, at the mean duration level, the length of the poverty spell for blacks is 17 months, which is more than twice the size of the effect from the OLS. Again, censoring marginally affects the coefficients.

We note that in most cases the results of the OLS (first column) lie between the results from both the log duration model and Weibull model. OLS also fares relatively well as measured by the median of MSE. Even though we acknowledge that a properly selected and estimated duration model is more appropriate for modeling a poverty spell length than a simple OLS, we believe that an arbitrarily selected duration model may cause more harm than good for our purpose of modeling the conditional effects.

5.5 Summary

We have asked how individual and community factors influence the average length of poverty spells. We use the term community factors to describe two distinct phenomena: local economic conditions, and neighborhood spillover effects. We measure local economic conditions using the county's unemployment rate. We measure neighborhood spillover effects using the racial makeup and poverty rate of the county.

Our matched PSID/Census sample covers the period 1968 to 1989 and includes all poverty spells greater than 12 months. The average poverty spell is nearly 39 months. The average black poverty spell length is 16 months longer than the average white poverty spell. The average female-headed household poverty spell is nine months longer than that of male-headed households. High School graduate households suffer 12 fewer months of poverty than dropout households. However, when we control for the demographic, human capital, and county level effects we find that the relative high school graduate poverty spell falls by 85 percent (two months), black poverty spells are halved (eight months), and female-headed households poverty spells fall by only about 20 percent (eight months).

Consistent with a life-cycle explanation, we find that for both races the poverty spell length falls in childhood, rises in adulthood and falls again after retirement. Using separate

equations for whites and blacks we find important differences in the factors (other than age) that influence poverty spells across races. Individuals in black, female-headed households suffer an additional nine months of poverty, while individuals in white, female-headed households suffer only four additional months of poverty. Living with a young head shortens the average black poverty spell by more than six months while living with a young head shortens poverty spells for whites by only about three months.

We consider the effect of a county's unemployment rate, poverty rate and racial makeup on the length of a poverty spell. Of the three factors, the percentage of poor in a county has the largest effect. Taken as a causal effect, moving an individual from one standard deviation above the mean poverty rate to one standard below the mean poverty rate (from the inner city to the suburbs) lowers the average poverty spell by 20–25 percent, which is equal to the effect of changing the household head from female to male.

Additional Reading

Bayer, P., S. L. Ross, and G. Topa (2008), "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes," *Journal of Political Economy*, 116, 1150-1196.

Bayer, P., F. Ferreira, and R. McMillan (2007), "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 115, 588-638.

Dujardin, C. and F. Goffette-Nagot (2010), "Neighborhood Effects on Unemployment? A Test at la Altonji," *Regional Science and Urban Economics*, 40, 380-396.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007), "Experimental Analysis of Neighborhood Effects," *Econometrica*, 75, 83-119.

6. Labor Supply Social Interactions: Estimates and Tax Policy Implications

Social interactions, the situation where individuals respond to the actions of people with whom they identify, may have a biological basis or stem from information gathering. Social interactions are a potentially important aspect of labor supply behavior; 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 members of a reference group. We find evidence of a positive spillover effect in hours worked and demonstrate their quantitative importance for tax policy (Grodner and Kniesner 2008c).

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 can be important because policy affecting the wages or another independent variable of a subgroup will not only affect the individual but also 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 examining 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 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 let us consider a basic proportional tax reduction applied to married men in a case 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 or interact regularly in professional settings. 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. We explore an econometric model that 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 using the mean of hours worked for persons 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 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. Our 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 the endogenous interactions component 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.

6.1 Conceptual Framework and Econometric Model

Theories of social interactions have a fairly long history in the economic literature. Becker (1974) fleshes out the consequences of when 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 or identifies. More recent theoretical research delves into the details of

how information and species survival considerations may be the source of equilibrium social interactions in utility (Samuelson 2004; Rayo and Becker 2007a,b) and what differentiates situations where individuals emulate versus deviate from peer behavior (Clark and Oswald 1998, Grodner and Kniesner 2006).

The utility function that leads to our labor supply estimating equation is the utility function derived by Hausman (1980, 1981) amended to include social interactions, which yields a linear labor supply function that is linear in the means of the reference group behavior. This anchors 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 average 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).

When implementing econometrically the spillover model of individual labor supply we estimate the familiar linear in means model that is the canonical linear labor supply model with social interactions added (Brock and Durlauf 2001, 2002, and Grodner and Kniesner 2006). Specifically, for individual i in reference group g

$$h_i = \theta + \alpha\omega_i + \beta v_i + \gamma x_i + \delta_1 \bar{h}_{(-i)g} + \delta_2 \bar{x}_{(-i)g} + \varepsilon_i, \quad (6.1)$$

where ω is the after-tax real wage, v is after-tax virtual income, x is a vector of individual control covariates, $\bar{h}_{(-i)g}$ is reference group g 's average labor supplied excluding the i^{th} worker, $\bar{x}_{(-i)g}$ is the vector of control covariate averages for the reference group excluding the i^{th} worker, ε is the error term, and $[\theta, \alpha, \beta, \gamma, \rho, \delta_1, \delta_2]$ are parameters to estimate. From equation (6.1), an increase

in average hours worked in the reference group spills over so that the individual also increases hours worked.

We now flesh out the econometric details involved with examining possible exogenous and endogenous social interactions in individual labor supply and suggest an approach that synthesizes two avenues in the literature. The econometrically inclined reader will immediately see the connection between social interactions issues and spatial econometrics (LeSage and Pace 2009).

6.2 Labor Supply Variables

The net wage rate (ω) uses a marginal tax rate τ provided by the PSID, and is $\omega = (1 - \tau)w$. Virtual income (ν) also uses the marginal tax rate from the PSID.¹⁵ To control for possible endogeneity when estimating (6.1) we instrument both the after tax wage and virtual income using the previous 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.

15. $\nu = [\text{NLI} + (\tau - (\text{TT}/(\text{TI} - \text{NLI})) \times (\text{TI} - \text{NLI}))]$, where NLI is non-labor income, TT are total taxes, and TI is taxable income (Ziliak and Kniesner 1999). For a survey of income tax effects on labor supply, including over the life cycle, see Kniesner and Ziliak (2008).

6.3 Social Interactions Variables

The mean labor supplied by the reference group is the sample average of hours worked for other people who are economically close to the worker. In 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.

Next, we create a proxy variable summarizing the information in the exogenous covariates. Specifically, we use factor analysis and take the first factor as a proxy variable for exogenous information. The new variable is standardized to have zero mean and unit variance, and is highly correlated here with all the exogenous variables as well as the individual's hours worked. The mean in the reference group for the created (factor analytic) proxy variable uses the same range of the economic distance variables as we use 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 will indicate any presence of exogenous social interactions.

6.4 Identifying Labor Supply Social Interactions

The labor supply equation in (6.1) can identify the presence of both endogenous (in the dependent variable) and exogenous (in the independent variables) social interactions. 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 (Manski 1993, 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, LeSage and Pace 2009).

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.¹⁶ 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 than with any other IV application.

Figure 6.1 illustrates our particular identification strategy. We present the hypothetical two-dimensional social coordinate space with two reference groups: g_1 and g_2 . Suppose that individual $h_{g_1}^0$ belongs to the reference group g_1 and responds to the outcomes of the members

16. Similarly, Case and Katz (1992) instrument for the endogenous effect using the average levels of adjacent neighbors' characteristics that are supposedly exogenous, and Evans et al. (1992) instrument school composition with city-wide variables for the unemployment rate.

of the reference group, represented by the observations labeled as $h_{g_1}^1$ and $h_{g_1g_2}^2$ (empty and shaded circles). If we use the mean of all $h_{g_1}^1$ and $h_{g_1g_2}^2$ observations (referred further as $\bar{h}_{g_1}^{(-0)}$) as an independent variable in the regression (6.1) to try to identify endogenous social interaction in $h_{g_1}^0$ the coefficient will be biased. Observations $h_{g_1}^1$ and $h_{g_1g_2}^2$ are also affected by outcome $h_{g_1}^0$, which causes endogeneity in the $\bar{h}_{g_1}^{(-0)}$. However, if there are observations in the reference group g_1 that also belong to the neighboring reference group g_2 , then part of $\bar{h}_{g_1}^{(-0)}$ attributed to the outcomes $h_{g_1g_2}^2$ can be instrumented by the outcomes of the members of the reference group g_2 , denoted by $h_{g_2}^3$. 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. The $h_{g_2}^3$ are valid instruments because they are correlated with all $h_{g_1g_2}^2$ observations since they belong to the same reference group, and $h_{g_2}^3$ are not correlated with the error terms associated with either $h_{g_1}^0$ or $h_{g_1}^1$ observations since they do not belong to the same reference group.¹⁷

17. In practice, if we instrument observations $h_{g_1g_2}^2$ with outcomes $h_{g_2}^3$ there may still be observations $h_{g_1}^1$ that are not instrumented and thus will make a part of the $\bar{h}_{g_1}^{(-0)}$ endogenous, which is the case presented in Figure 6.1. 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).

6.5 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 chose 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.

6.5.1 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).¹⁸

18. 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

6.5.2 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 is 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).

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.

6.5.3 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 different 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 (6.1). 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.¹⁹ 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.

6.6 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 (6.1) 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.

19. 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.

6.6.1 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 6.1). 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).²⁰ 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 social interactions are 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 (6.1) to become negative as the neighborhood size increases (Anselin 2001). The reference group with

20. 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.

the most positive $\hat{\delta}_1$ in exploratory estimates of (6.1) then reveals the size of the worker's reference group.

Grodner and Kniesner (2008c) presents results from baseline labor supply regressions with a social interactions variable, `AnnHSRG_0_R`. Estimation starts with radius indicator $R = 1$, 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.

As expected a priori, the coefficient on average hours worked by neighboring persons is increasingly negative, 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 (Kelejian and Prucha, 2002). Critical to our research is that the reference group labor supply coefficient is most significantly positive at the size of the reference group where radius indicator $R = 2$.

The pattern of background regressions in Grodner and Kniesner (2008c) 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) support the presence of social interactions in hours worked; the radius we adopt to define the reference group based on our preliminary regressions also maximizes the Moran I statistic measure of association. The practical consequence of our specification search is that the average reference group contains about 44 persons, which indicates to us that groups are 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 (standard deviation is 38 and maximum size is 139).²¹

6.6.2 Estimated 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 6.1 presents IV regression wage and income coefficients for the canonical model of labor supply. The uncompensated wage elasticity at the means is 0.14, and the income elasticity at the means is -0.008 ; both values are typical estimates in the male cross-section 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 6.1, where we include both habits and social interactions. We also use as a regressor the average of the proxy

21. As yet another check on the reasonableness of how our econometric model reveals groups, we examined the intragroup correlation of the members' characteristics variables and the correlation of the same variables in an identical sized group selected randomly. In all cases the model's groupings had much higher intragroup correlations (typically greater than $+0.90$) versus among the members of randomized groups of similar size (typically less than $+0.02$).

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 6.1 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.²²

It is important to re-emphasize that the estimated endogenous 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 economically reasonable magnitude only after the we instrument for interdependence, which we do in Table 6.1 (the Durbin-Wu-Hausman test rejects exogeneity at the 5 percent level). Because the econometric issues in social interactions/spatial economics models are still unfamiliar to many readers the method we use to construct the instrument for social interactions in labor supply bears re-emphasis.

22. The coefficient on the hours worked for the reference group needs to be less than 1.0 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 would cause a domino effect where, in the limit, all workers choose the maximum feasible hours. The coefficient of the lagged dependent variable in both columns (2) and (3) is 0.59 with a standard error of 0.03. In a cross-section regression it will reflect both habits and additional worker-specific heterogeneity. One needs an IV panel data estimator to incorporate both two effects into the model properly, which is an interesting topic for future research.

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 two-dimensional 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.²³ We construct hours worked by individuals in the outside ring in Figure 6.1, (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 6.2 confirm that our instruments (for all three right-hand side endogenous regressors: after-tax wage, virtual income, and reference group average labor supplied) are valid in terms of passing the standard checks for instrument strength and overidentifying restrictions. Equivalently, the strength of our identifying instruments here means that the potential bias of the IV estimator of the endogenous social interactions effect in Table 6.1 is small: less than 4 percent of the potential bias of OLS (Hahn and Hausman 2003; Stock and Yogo 2005).

6.6.3 Additional Econometric Validity Checks of the Reference Group

In Grodner and Kniesner (2008c) we 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 6.1, which leaves the reference group size the same but decreases the number of observations viewed as nearest

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

neighbors for the reference group, or change by (2) shrinking the inner reference group circle boundary in Figure 6.1, 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 also 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 summarized the sensitivity of our results to instrument set as discussed in Grodner and Kniesner (2008c) we now turn our attention to the economic interpretation and policy implications of our estimated social interactions effects in male labor supply.

6.7 Interpreting the Importance of the Estimated Social Interactions Effect

Social interactions in labor supply mean that individuals respond to others' hours worked by an economically significant 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 consider 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 (Kniesner and Ziliak 2008).

Taking the mean values in equation (6.1) and focusing on hours worked and wages,

$$\bar{h} = \alpha\bar{\omega} + \delta_1\bar{h} \Rightarrow \bar{h} = \alpha \frac{1}{1-\delta_1} \bar{\omega}, \quad (6.2)$$

where $1/(1-\delta_1)$ 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 uncompensated effect of a wage change in the static linear model can be decomposed into

$$\frac{\partial \bar{h}}{\partial \bar{\omega}} = \frac{\alpha}{1-\delta_1} = \alpha + \frac{\alpha\delta_1}{1-\delta_1}, \quad (6.3)$$

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 (6.3) by $\bar{\omega}/\bar{h}$ the uncompensated elasticity is

$$\eta_{hw,total} = \eta_{hw,exogenous} + \eta_{hw,endogenous}, \quad (6.4)$$

where $\eta_{hw,exogenous} = \alpha\bar{\omega}/\bar{h}$ and $\eta_{hw,endogenous} = \alpha\delta_1\bar{\omega}/(1-\delta_1)\bar{h}$. 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 (6.4) 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 6.1, the total uncompensated wage elasticity of labor supply at the means is 0.22, with an exogenous part of 0.08 and an endogenous part of 0.14. In comparison, the baseline model results from column one of Table 6.1 are an uncompensated net wage elasticity of 0.13. If 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.

6.8 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 the endogenous interactions component one underestimates the wage elasticity by over 60 percent.

It is less obvious how we should apply estimates where the policy-maker considers wage elasticity 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 6.1, 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).

How can one use our decomposition of the total wage elasticity into its exogenous component (+0.08) and its endogenous social interactions component (+0.14) in policy calculations? 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 or interact regularly in business. 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.

6.9 Summary

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 who are economically close to each other. Our measure of economic distance uses factor analysis, which allows mapping multiple economic 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 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-applied can easily lead to mis-estimates of the labor supply effects of tax reform by as much as 60 percent.

Additional Reading

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7. Conclusion

Our goal has been to present a unified theoretical and empirical representation of social interactions as they pertain to labor supply and demand and demonstrate cases where current policy prescriptions are greatly altered by the presence of social interactions.

We began by examining theoretically in Section 2 the issues of how a researcher estimates and subsequently interprets labor supply (and by extension earnings) equations. We considered a positive spillover from others' labor supplied versus a possible need for conformity with others' labor supplied. Qualitative and quantitative comparative statics results revealed how spillover effects increase labor supply and earnings uniformly while conformity effects move labor supplied toward the mean of the reference group so that labor supply becomes perfectly inelastic at a reference group average. We showed that when exogenous social interactions may be ignored, conventional wage elasticities are still relatively well estimated although structural parameters may not be. Omitting endogenous social interactions may seriously misrepresent the labor supply effects of policy.

We next considered social interactions in demand side where the household's demand for a good may be influenced by either a spillover effect from other consumers' choices or a conformity effect representing a need for making choices similar to others'. A positive spillover effect increases the demand for the good with interactions, and a conformity effect makes the demand curve pivot to become less price elastic. Spillover in consumption also increases the associated derived demand for labor while conformity in consumption makes the associated derived demand for labor less elastic. As in the case of labor supply social interactions can make us rethink policies to influence worker well-being via labor demanded.

An important aspect of labor market outcomes is how individual and community factors may influence the average length of poverty spells in ways that can complement (or counteract) income maintenance programs. We considered local economic conditions as reflected by the county unemployment rate and neighborhood spillover effects as reflected by the racial makeup and poverty rate of the county. Moving an individual from one standard deviation above the mean poverty rate to one standard deviation below the mean poverty rate (from the inner city to the suburbs) lowers the average poverty spell by 20–25 percent; the poverty spillover effect is equal in magnitude to the effect of changing the household head from female to male.

We examined overall labor market outcomes and related economic policy further by modeling theoretically the socially optimal wealth distribution in a two-person two-good model with heterogeneous workers and asymmetric social interactions where only one (social) individual derives positive or negative utility from the leisure of the other (non-social) individual. The interdependence in utility can mitigate the need to transfer wealth to low-wage individuals and may leave them to be poorer by all objective measures. We do not claim that this is the most general situation but rather use it to demonstrate how social interactions complicate thinking about economic policy.

Lastly, we generalized how economic policy issues related to labor market outcomes are changed when there are household social interactions to consider and examine econometrically what we know about the importance of household interactions. After fleshing out the econometric details of implementing an empirical model with possible social interactions in labor supply we looked for a response of a person's hours worked to hours worked in the labor market reference group, which includes those with similar age, family structure, and location. We identify endogenous spillovers by instrumenting average hours worked in the reference

group with hours worked in neighboring reference groups. Estimates of the canonical labor supply model indicate positive economically important spillovers for adult men. The estimated total wage elasticity of labor supply is 0.22, where 0.08 is the exogenous wage change effect and 0.14 is the social interactions effect. Ignoring or incorrectly considering social interactions can mis-estimate the labor supply response of tax reform by as much as 60 percent.

**Table 4.1. Effect of Heterogeneous Wage and Social Interactions in Worker 1 on the Optimal Distribution of Wealth.
Positively Social Individual Is A Low Wage Worker (Delta = 0.01, Wage For Non-Social Worker [2] = 0.8702)**

		Equal Wealth Distribution				Optimal Wealth Distribution				Percent Welfare Loss due to Equality
		Wealth 1 /Wealth 2	Earnings 1 /Earnings 2	Income 1 /Income 2	Utilities 1 /Utilities 2	Wealth 1 /Wealth 2	Earnings 1 /Earnings 2	Income 1 /Income 2	Utilities 1 /Utilities 2	
Wage for Worker 1	0.6500	1.000	0.549	0.665	1.064	5.793	0.362	0.813	1.166	-0.126
	0.7000	1.000	0.647	0.738	1.074	2.073	0.546	0.813	1.122	-0.029
	0.7500	1.000	0.749	0.813	1.084	1.000	0.749	0.813	1.084	-0.000
	0.7700	1.000	0.790	0.844	1.088	0.758	0.835	0.813	1.070	-0.004
	0.8000	1.000	0.852	0.890	1.094	0.489	0.973	0.813	1.051	-0.025
	0.8500	1.000	0.957	0.968	1.105	0.190	1.224	0.813	1.022	-0.095
	0.9000	1.000	1.064	1.048	1.115	-0.007	1.507	0.813	0.996	-0.200

**Table 4.2. Effect of Heterogeneous Wage and Social Interactions in Worker 1 on the Optimal Distribution of Wealth.
Negatively Social Individual Is A High Wage Worker (Delta = 0.01, Wage For Non-Social Worker [2] = 0.66319)**

		Equal Wealth Distribution				Optimal Wealth Distribution				Percent Welfare Loss due to Equality
		Wealth 1 /Wealth 2	Earnings 1 /Earnings 2	Income 1 /Income 2	Utilities 1 /Utilities 2	Wealth 1 /Wealth 2	Earnings 1 /Earnings 2	Income 1 /Income 2	Utilities 1 /Utilities 2	
Wage for Worker 1	0.6500	1.000	0.955	0.972	0.874	19.423	0.488	1.301	1.031	-0.265
	0.7000	1.000	1.127	1.079	0.884	3.963	0.767	1.301	0.983	-0.109
	0.7500	1.000	1.303	1.189	0.894	1.843	1.094	1.301	0.941	-0.025
	0.7700	1.000	1.374	1.234	0.899	1.431	1.241	1.301	0.926	-0.009
	0.8000	1.000	1.483	1.301	0.905	1.000	1.483	1.301	0.905	-0.000
	0.8500	1.000	1.666	1.416	0.916	0.547	1.955	1.301	0.873	-0.022
	0.9000	1.000	1.852	1.532	0.927	0.263	2.540	1.301	0.845	-0.082

Table 5.1. Months in Poverty by Demographic Characteristics

	All	All	White	Black
Black	8.3241 (0.5753)***	7.8052 (0.6576)***		
Female	1.6211 (0.4719)***	1.5908 (0.4710)***	1.1428 (0.6309)*	1.9586 (0.6461)***
Femalehead	7.4910 (0.9141)***	7.6976 (0.9118)***	3.9786 (1.1966)***	9.4335 (1.2695)***
heduc_high	-2.2339 (0.5511)***	-1.9627 (0.5506)***	-1.1465 (0.7116)	-2.4839 (0.7735)***
agehead_0_25_	-4.9571 (0.6443)***	-4.8393 (0.6433)***	-2.6901 (0.8178)***	-6.2327 (0.9137)***
agehead_60_	0.4824 (0.9360)	0.4601 (0.9359)	2.0198 (1.3107)	1.4148 (1.2736)
Married	1.3237 (0.8969)	1.1952 (0.8956)	1.2649 (1.1290)	0.9186 (1.2706)
County variables	no	yes	yes	yes
Cubic age	yes	yes	yes	yes
Moving indicators	yes	yes	yes	yes
Censoring variables	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
State dummies	yes	yes	yes	yes
Observations	27083	27020	8657	17227
R-squared	0.2762	0.2820	0.2685	0.2861
Average poverty length #	38.73692 (43.22962) [.2626836]	38.7544 (43.25611) [.2631508]	28.36364 (31.3008) [.3364122]	44.46485 (47.85173) [.36458]

reports mean, standard deviation, and standard error

* - significant on 10% level, ** - significant on 5% level, *** - significant on 1% level

Table 5.2. Marginal Effects Using Parametric Duration Models (All Observations)

	OLS	right-censored OLS	right-censored log OLS	Uncensored Weibull duration	Censored Weibull duration
Black	7.8052*	6.8824	6.2969	17.5725	17.9110
Female	1.5908*	0.4244	0.3618	2.8017	1.8383
Femalehead	7.6976*	4.8837	5.1284	16.0670	13.2217
heduc_high	-1.9628*	-2.3328	-3.0057	-3.9571	-4.1564
agehead_0_25_	-4.8393*	-5.8914	-5.2903	-9.4923	-11.8167
agehead_60_	0.4601	-1.4906	-0.5676	1.5212	0.1311
Married	1.1952	-0.8606	-0.9543	2.5254	-0.9909
% unemp	0.9334*	0.6754	0.6704	1.8992	1.8938
% unemp^2	-0.0367*	-0.0100	-0.0115	-0.0486	-0.0169
% black	0.2032*	0.1808	0.0954	0.5039	0.4967
% black^2	-0.0053*	-0.0043	-0.0024	-0.0112	-0.0096
% poor	0.6383*	0.5027	0.4831	1.3564	1.4126
% poor^2	-0.0004*	-0.0010	-0.0010	-0.01014	-0.0130
Observations	27020	27020	27020	27020	27020
median MSE	293.49	461.76	521.03	230.06	412.61

Note1: we report only coefficients because the standard errors may not be comparable between models and we could not obtain them for the Weibull specification.

Note2: 9238 spells are right censored.

* - significant on 5% level

Table 6.1. 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* (35.5604)	38.5373 (28.6798)	30.5734 (28.1246)	81.6429** (37.3766)
VirtualInc	-0.0031 (0.0058)	0.0000 (0.0047)	0.0011 (0.0045)	-0.0055 (0.0061)
IndVRG_0_2	-318.8201 (381.9788)	-317.4740 (307.9343)	-284.0008 (302.0874)	-385.0609 (401.1535)
AnnHSRG_0_2		0.6379** (0.2689)		1.3128*** (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. $F(\text{Shea partial } R^2) = 53.0(0.189), 368.1(0.621), 51.9(0.188)$

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 2.1. Baseline and Spillover with $\mu_h = 2172$, $\theta = 0.113$

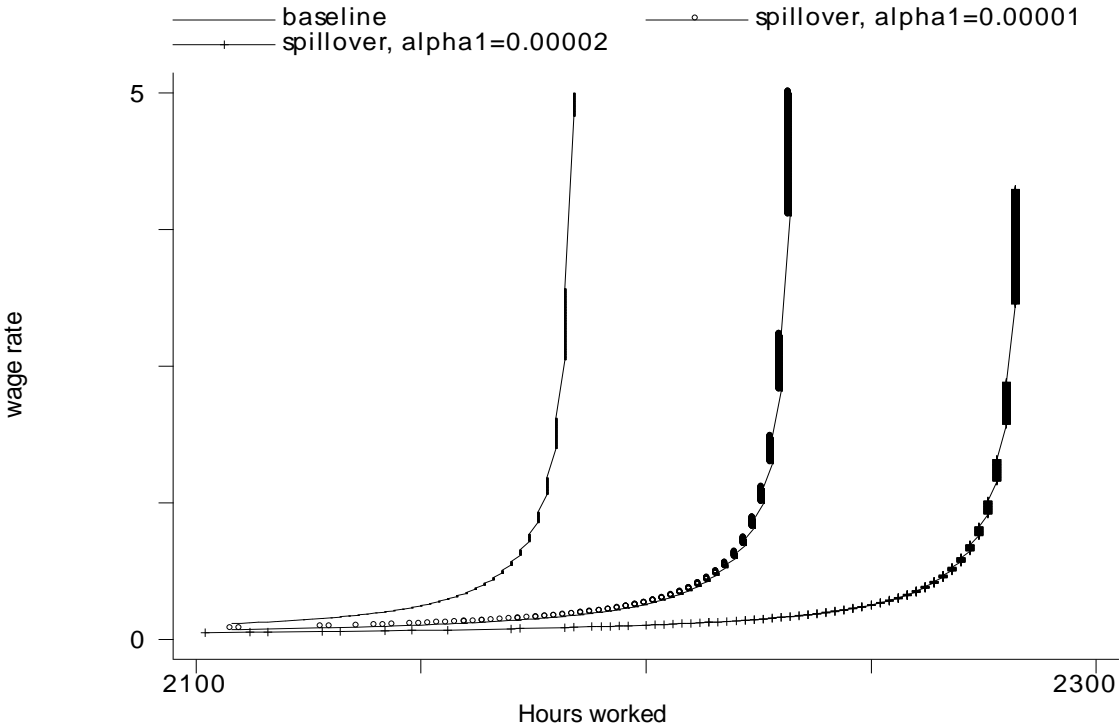


Figure 2.2. Baseline and Conformity with $\mu_h = 2172$, $\theta = 0.113$

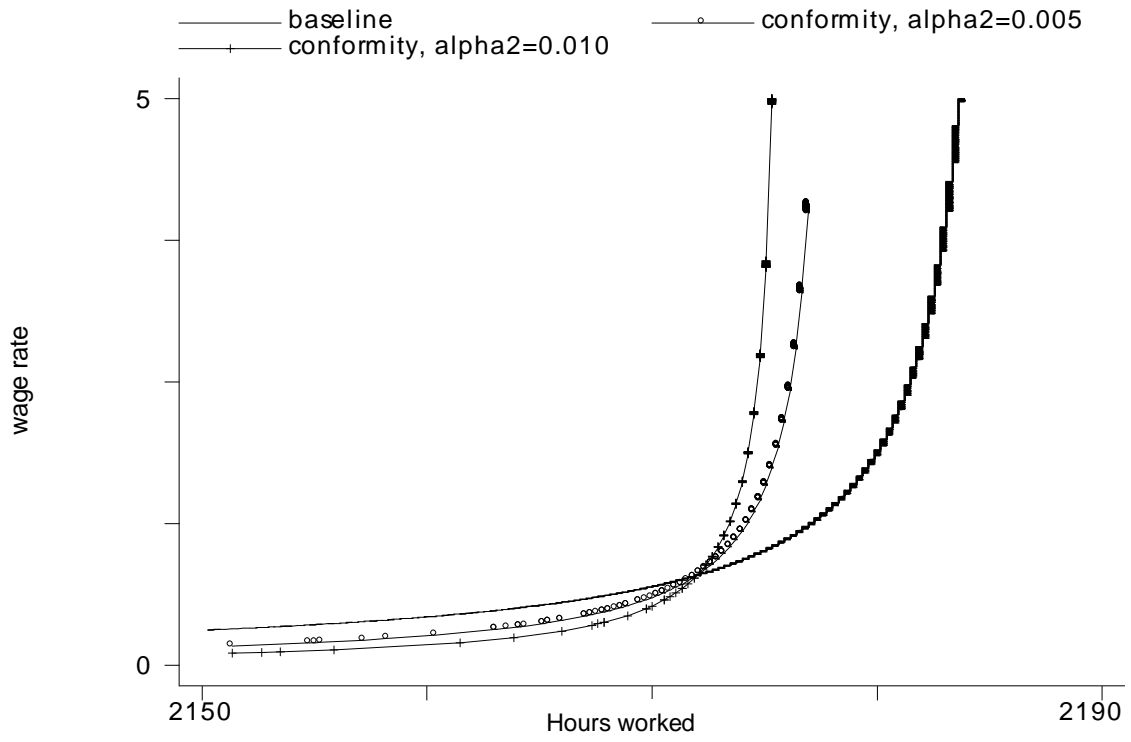


Figure 2.3. Labor Market Equilibrium When There Are Endogenous Versus Exogenous Social Interactions in Hours Worked Caused By a Spillover Effect

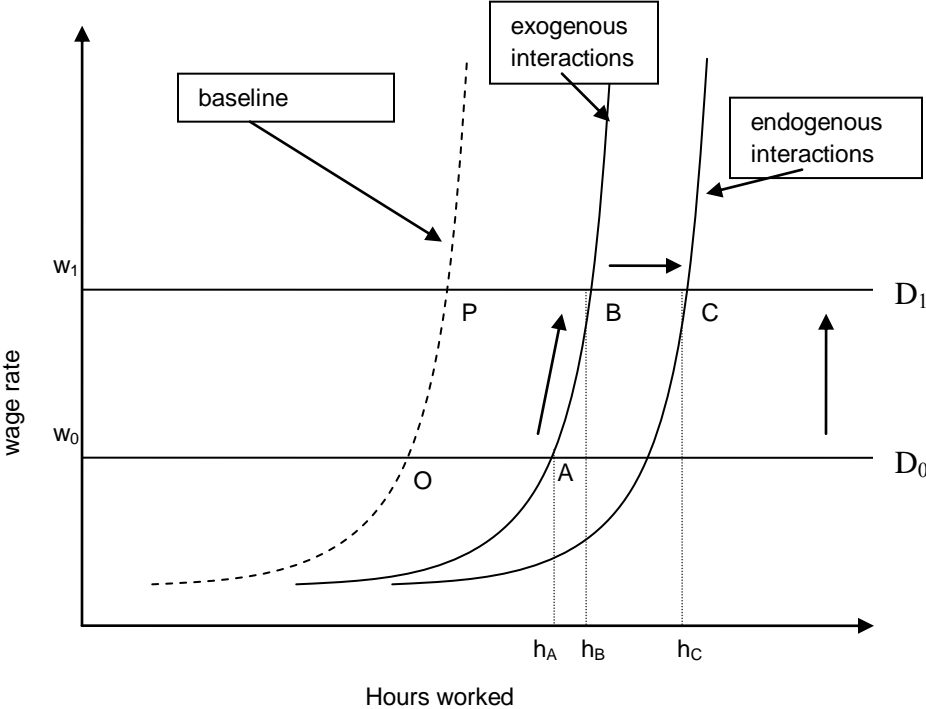


Figure 3.1. Demonstration of the effect of the spillover interactions on the demand for good x with different functional forms

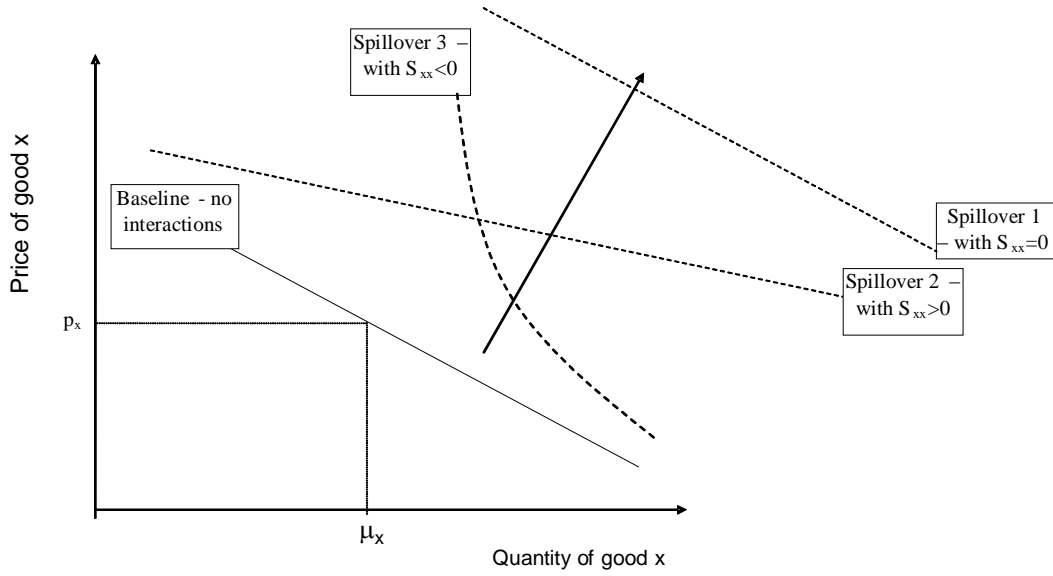


Figure 3.2. Demonstration of the Effect of the Conformity Interactions on the Demand for good x with Different Functional Forms

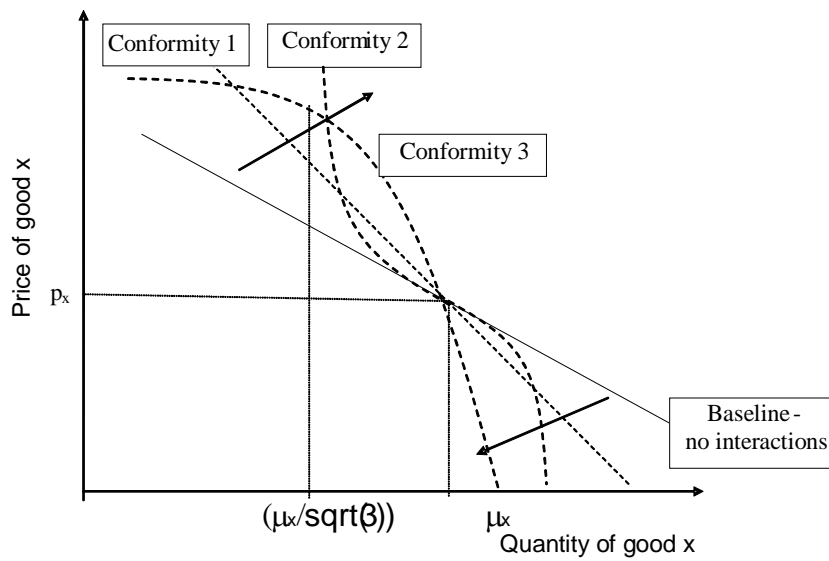


Figure 3.3. Demonstration of The Effect of the Conformity In good x on the Demand for good y When There Is An Extreme Conformity In good x (Consumer Fixed Amount of good x); Graphs Represent Relationship Between Offer

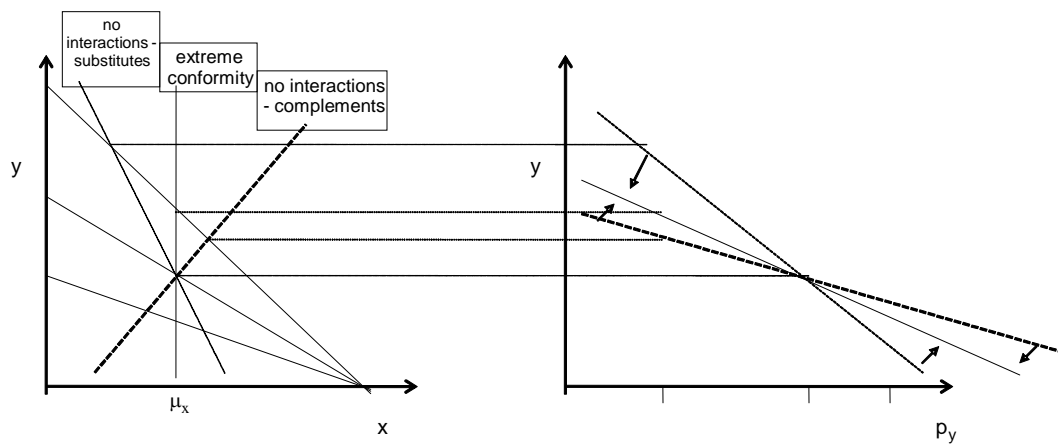


Figure 5.1a. White

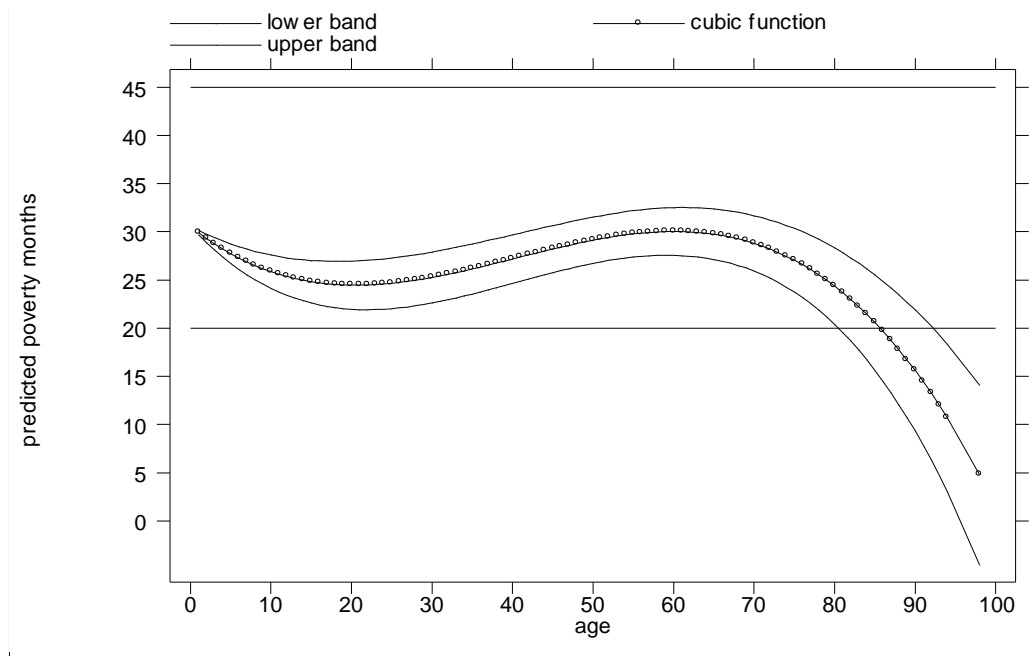


Figure 5.1b. Black

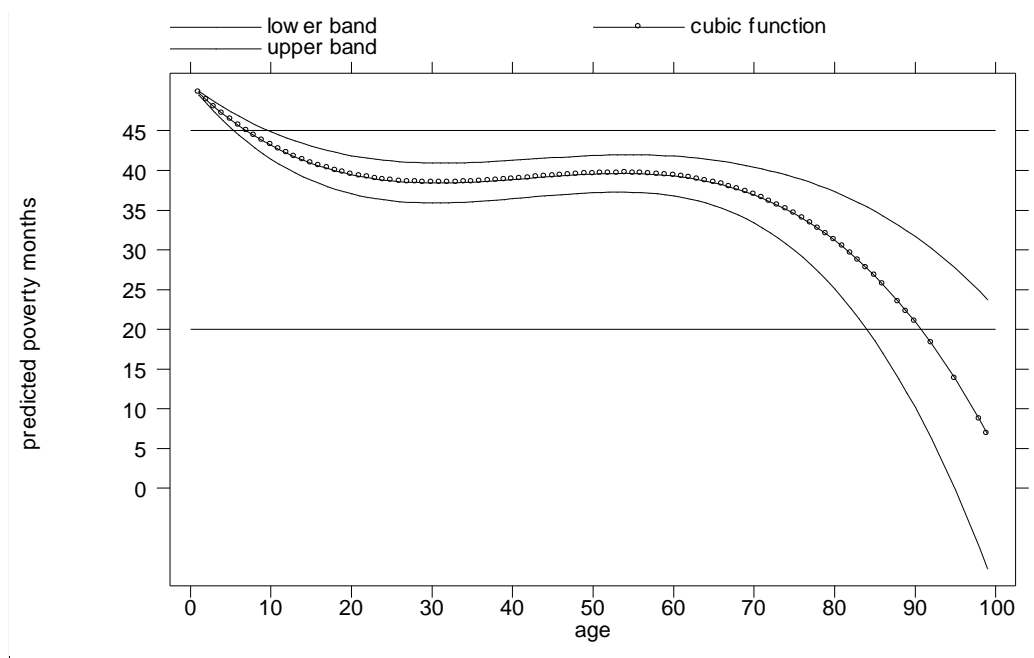


Figure 5.2a. White

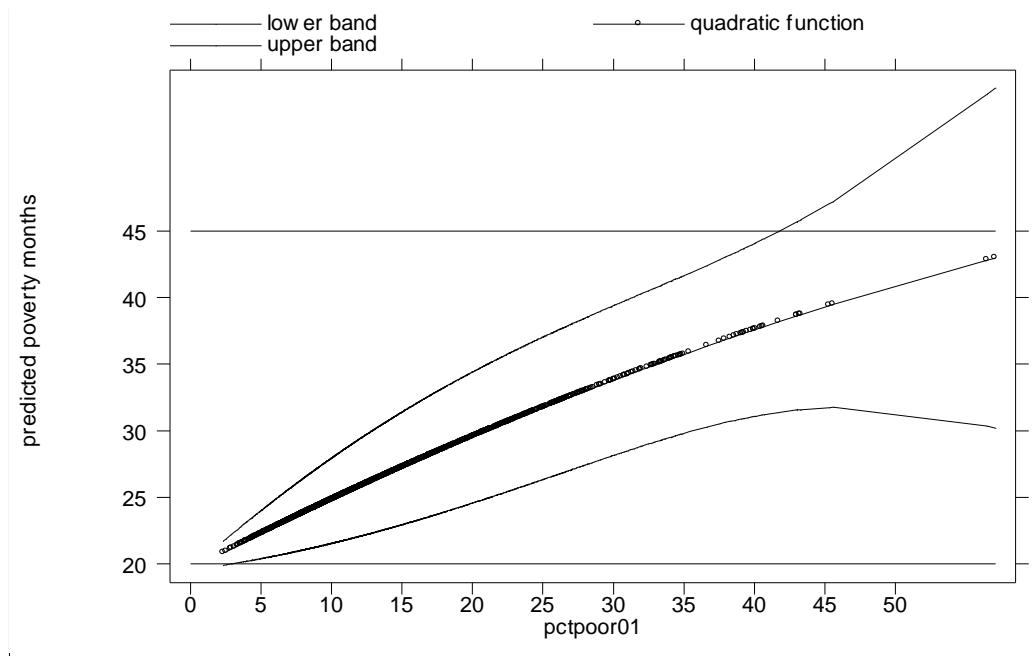


Figure 5.2b. Black

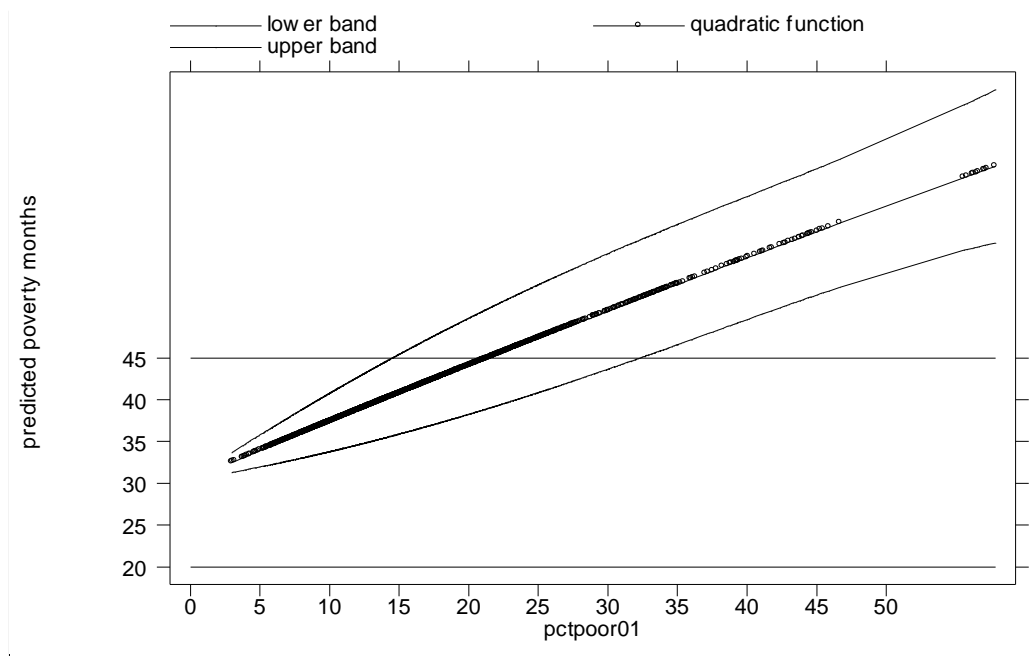
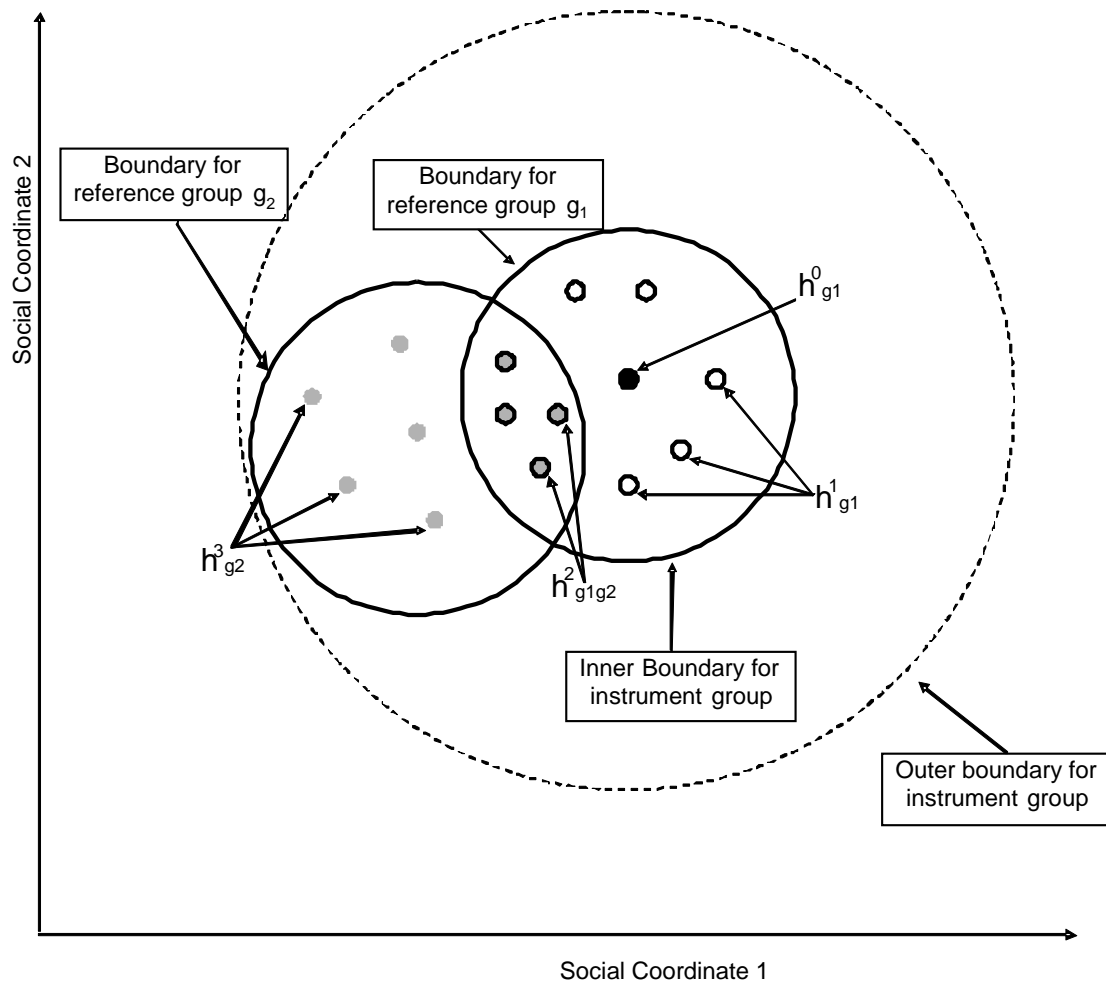


Figure 6.1. Demonstration of the Identification Strategy for the Endogenous Social Interactions.



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