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Welfare Stigma or Information Sharing? Decomposing Social Interactions Effects in Social Benefit Use

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Abstract - Empirical research has shown that social interactions affect the use of public benefits, thus providing evidence in favor of the idea of "welfare cultures." In this paper we take the next crucial step by separately identifying the role of social stigma and information sharing in welfare participation, using Census data. We argue that the stigma vs. information distinction has possibly important consequences. Separate identification exploits the asymmetry between association and mere spatial proximity: we asume that while information is transmitted within groups, stigma works across groups as well. We also allow for heterogeneity of social effects across different race-ethnic groups and find non-trivial differences. We find that while the information channel is more important than stigma, White Americans appear to perceive stigma more from otherWhite Americans than by other races, and Black and Hispanic Americans appear to respond principally to stigma from external groups.

JEL Classification Codes: I30, Z13.

Keywords: social interactions, neighborhood effects, welfare stigma.

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1 Introduction

During the past 25 years the cost of social safety nets, broadly writ, has been steadily increasing in OECD countries. Table 1 shows that public social expenditure increased by about 5 percentage points of GDP since the 1980s. Such a dynamics has naturally generated debate on the use of welfare programs, and particularly on the demographic and social patterns of take-up rates. A range of recent research has focused on social effects in welfare use as a possible explanation. At the theoretical level, the idea is that interacting with people on welfare may increase the likelihood of becoming welfare dependent, so that participation in social safety nets depends not only on individual risk factors, such as being poorly educated, disabled or being a single young mother, but also on the social context. For instance, Rege *et al.* (2007) find that these peer effects explain high usage rates for disability insurance in Scandinavia, and Bertrand *et al.* (2000) find that they account for the emergence of "welfare cultures" in the US.

In the context of this literature, two main channels of social influence have been posited. First, being surrounded by many people receiving public assistance decreases the embarrassment of doing likewise [Moffitt (1983); Lindbeck *et al.* (1999)]. This is the *stigma channel*. Second, people may be influenced about their welfare choice through the receipt of information on eligibility, application procedures, bureaucratic details and the like with acquaintances, as well learning from the choices of people they interact with. This allows one to overcome information barriers, which have been shown to prevent program participation [Heckman and Smith (2003); Aizer (2007)]. This is the *information channel*. These two channels work in the same direction, i.e. predict a positive relation between the likelihood of using welfare and the welfare participation rate, so it is hard to distinguish them. On the other hand, such a distinction is important because different channels through which social interactions operate have very different policy implications. Yet, existing empirical work by and large bypasses the question of disentangling these different effects.[1] In this paper we aim at filling this gap, i.e. identify separately stigma and information effects in welfare participation, through a simple general procedure.

Social psychologists have long distinguished between these two forms of social influence. Campbell and Fairey (1989), define *normative social influence* as "influence to conform to the positive expectation of behavior," and *informational social influence*, as "influence to accept information obtained from another as evidence about reality." The mapping here is useful in that we can draw on decades

[1] An exception is Aizer and Currie (2004), who use Vital Statistics data from California to estimate network effects in the use of public prenatal care. The authors argue that such an effect is unlikely to be due to information sharing, but do not quantify the relative magnitude of stigma and information.

of work in social psychology in order to understand how individuals may be using information on others' welfare decisions to make their own choices. Below, we extend this parallel in justify our separation methodology.

Our strategy proceeds as follows. We use a sample of American women of working age, from Census microdata. Reference groups are defined along race-ethnic lines at the PUMA level.[2] We achieve identification of the total social effect by isolating in our dataset a plausible individual effect whose average is not a source of contextual effects. Such a restriction allows us to avoid the "reflection problem" in a clean way [see Manski (1993) and Brock and Durlauf (2001)]. Separation is achieved by arguing that different groups within PUMAs are associated with different social effects.[3] Specifically, we assume that information is shared within reference groups, while stigma works both within and across groups. In other words, while *social proximity* is necessary for information sharing, mere *spatial proximity* is sufficient for stigma.[4] We discuss this assumption is greater detail in the next Section. From a technical perspective, we simply estimate two social effects. One of these is a race-ethnicity specific effect and the other is a general PUMA-level effect. It is by drawing on the social psychology literature that we propose that these effects can be labeled 'information' and 'stigma'. More discussion is found below, but henceforth, we will refer only to these labels.

Our results can be summarized as follows. First, we find that the total social effect is significant and does not differ much across race-ethnic groups. Second, information is the dominant social effect for Black and Hispanic Americans, but of negligible importance for Whites. Third, to the extent that stigma matters, stigma from one's own group matters for White Americans but is negligible for Black and Hispanic Americans. For Blacks and Hispanics, we find that stigma from other groups is instead relatively more important. The resulting social multiplier is complex, in the sense that it results from a mixture of mechanisms that differ across races.

The remainder of the paper is organized as follows. In Section 2 we illustrate our theoretical framework. Section 3 presents our estimation strategy. Section 4 describes the dataset. In section 5 we present and discuss our results. Section 6 concludes.

[2]A PUMA (Public Use Microdata Area) is an area defined by the US Census Bureau, with a minimum population of 100,000 and an average around 150,000.

[3]This simple method is illustrated at a general yet simple level in Cohen-Cole and Zanella (2008).

[4]There is evidence that preferences for redistribution and perceptions of welfare are affected by the number of welfare recipients of one's own race-ethicity relative to other groups at the local level (e.g. Luttmer, 2001; Alesina and Glaeser, 2004).

2 Theoretical framework

To put our model into context, we draw on the two channels of social influence described above. Denote by π the welfare participation indicator in a static setting, consistent with our cross-sectional dataset. A risk-neutral individual must decide whether to work and live on labor income, in which case she does not use welfare ($\pi = 0$) and earns after-tax wage w, or not work and live on welfare ($\pi = 1$), in which case she receives a transfer T from the government. Of course $T = 0$ if the individual in question is not eligible for welfare. The transfer is financed by taxation, which we don't model as we confine our analysis to partial equilibrium. Each individual belongs to a geographic community that coincides with a location ℓ—PUMAs in our empirical investigation—as well as to a race-ethnic group, denoted r. The pair (ℓ, r) defines the individual's *reference group*, or *own-group*. That is, we incorporate a stylized fact that characterizes the American society: individuals associate within communities mostly on a race-ethnic basis.

By construction, reference groups are non-overlapping, so for each group r we can define a local *out-group*: this is the union of all other groups within the same community, and is denoted by subscript o. Living on welfare is associated with a participation cost, denoted by I. This is not necessarily an out-of-pocket cost: it is a simple way to capture the role of information, including the benefits of informational social influence. We define information operationally: more information leads to a reduced participation cost. Information can be spread institutionally (e.g. social workers in the US) or shared within reference groups defined by the pair (ℓ, r). In other words, while institutional information (denoted Ω^ℓ) is freely available in each location, information sharing requires *social proximity,* i.e. membership in the same reference group. The assumption that information is shared principally within race-ethnic groups, or more generally reference groups, is palatable to us, as well as supported by empirical evidence. In the US there is still a considerable amount of residential stratification along race-ethnic lines [Massey and Denton (1993); US Census Bureau (2002)]. Furthermore, this is is associated with a tendency to interact along these same lines: a telltale sign of this phenomenon is the formation of networks based on race-ethnicity at the school level even when schools are integrated [see Moody (2001)]. As a consequence, peer-to-peer information is more likely to be shared within but not across race-ethnic groups. Empirical work in development economics offers numerous examples. For instance, Romani (2003) finds that in Côte d'Ivoire information about new agricultural technologies flows within ethnic groups, but not across them. Similarly, Bandiera and Rasul (2006) find that in Mozambique farmers' decisions to adopt a new crop are correlated within religious groups, but not across religions. Munshi and Myaux (2006) find that information about contraception in rural Bangladesh is shared within religious group at the village level, with no cross-religion effect.[5]

The probability that a member of group r in location ℓ meets with someone who is on welfare in the same location is equal to the welfare participation rate in the reference group, denoted m_r^ℓ. This interpretation is possible because by definition of social proximity she is also a member of group r – the probability of social proximity being equal to 1 within a race-ethnic group in a given area. Therefore m_r^ℓ is a measure of information from social contacts, and the participation cost can be expressed as a function $I\left(\Omega^\ell, m_r^\ell\right)$ that is decreasing in both arguments.

Welfare participation leads to welfare stigma as well. Following Lindbeck *et al.* (1999), this is defined in a social sense as the punishment for the violation of the social norm "everybody should live by his own work."[6] Spatial *spatial proximity*, i.e. membership in the same community ℓ, is sufficient for this form of social interactions: in order to feel stigmatized by somebody it is enough to *feel* regarded with a negative characterization as welfare dependent. It follows from our definitions that *social proximity* implies *spatial proximity* but the reverse is not true. Therefore, stigma comes from both own- and out-groups. The degree of welfare stigma—being associated with a social norm—is plausibly endogenous and dependent on how common welfare use is, as well as on group membership. This mechanism is related to what Luttmer (2001) calls *negative exposure effect* and *racial group loyalty*:[7] while individuals tend to be unsupportive of welfare as many people in the community are recipients, they tend to be supportive when they belong to the same ethnic-racial group of the recipients themselves. Therefore, the more individuals that are on welfare in the community, the less embarrassing it is to receive public transfers. These ideas are captured by a *total stigma function* $S\left(m_r^\ell, m_o^\ell\right)$ that is decreasing in the welfare participation rates in both own- and out-groups, respectively.

Therefore, while own-group is a source of both stigma and information, out-groups are a source of stigma only. This will be our *separating* assumption. The utility function over the participation choice is:

$$U(0) = w \tag{1}$$

$$U(1) = T - I\left(\Omega^\ell, m_r^\ell\right) - S\left(m_r^\ell, m_o^\ell\right). \tag{2}$$

[5]In a different context, Duflo and Saez (2003) find that information that ultimately affects enrollment in a retirement plan is shared within but not across departments.

[6]This social definition extends Moffitt's (1983) introspective definition of stigma (a negative self-characterization due to lack of self-support).

[7]These are both equivalent to the finding of the research agenda on Social Identity Theory. For example, Yanovitsky *et al.* (2006) test such patterns and find similar support for these effects in their study.

An eligible individual uses welfare if and only if $U(1) \geq U(0)$. This defines a reservation wage, $\widetilde{w}_r^\ell$, for each reference group, as the solution to the indifference condition $U(1) = U(0)$:

$$\widetilde{w}_r^\ell = T - I\left(\Omega^\ell, m_r^\ell\right) - S\left(m_r^\ell, m_o^\ell\right). \tag{3}$$

An individual works if she can earn at least $\widetilde{w}_r^\ell$ on the labor market, and chooses welfare otherwise. Therefore, the equilibrium participation rates are defined by the fixed point that satisfies

$$\left(m_r^\ell, m_o^\ell\right) = F\left(\widetilde{w}_r^\ell\left(m_r^\ell, m_o^\ell\right)\right), \tag{4}$$

where F is the distribution of wages in the economy. An equilibrium in this model is a set of reservation wages for each group and participation rates such that utility is maximized. The equilibrium probability of welfare use, conditional on membership in group (ℓ, r), is

$$\Pr\left(\pi_{r\ell} = 1\right) = F\left(T - I\left(\Omega^\ell, m_r^\ell\right) - S\left(m_r^\ell, m_o^\ell\right)\right). \tag{5}$$

Since T is unobserved for individuals who could live on welfare but choose to work instead, we use individual characteristics X to form a linear prediction for this variable, $T = k^T + cX$, where k^T is a constant. Next, we specify $I(.)$ and $S(.)$ as linear:

$$\begin{aligned} I\left(\Omega^\ell, m_r^\ell\right) &= k^I - b\Omega^\ell - J_r^I m_r^\ell, & (6)\\ S\left(m_r^\ell, m_o^\ell\right) &= k^S - J_{ro}^S\left(\alpha_r m_r^\ell + (1-\alpha_r)\textstyle\sum_{\rho\neq r}\alpha_\rho^\ell m_\rho^\ell\right), & (7)\end{aligned}$$

where k^I and k^S are constants, α_ρ^ℓ is the demographic share of individuals of race-ethnic group ρ, $\rho \neq r$, in community ℓ and α_r is the national share of race-ethnicity r.

The rationale of equation (6) is intuitive: since m_r^ℓ can be regarded as the probability of meeting an individual with whom one is associated and who can pass information, J_r^I is the information effect from own-group keeping information from institutional sources, Ω^ℓ, constant.

The total stigma function (7) is composed of two parts that generate the stigma effect from own- and out-groups, J_{ro}^S. The first part is again the own-group welfare participation rate: the more likely an individual on welfare from own-group is met, the less one feels stigmatized if she is also on welfare. The second part aggregates single terms $\alpha_\rho^\ell m_\rho^\ell$ which can be interpreted as the probability that a member of group r in area ℓ meets a member of group $\rho \neq r$ who is on welfare. This is so because the probability of living in spatial proximity of an individual from race-ethnicity ρ in location ℓ is $\alpha_\rho^\ell < 1$. This interpretation justifies two apparent anomalies in equation (7). First, we don't need to normalize the weights so that they may sum to 1. Second, the own-group effect does not vary with the size of the reference group, while the out-group effect does. This is a consequence of the difference between spatial and social proximity. The two parts are weighted to allow stigma from own-group and aggregate stigma from all out-groups to be substitutes at a rate different from one. We choose national shares α_r and $(1-\alpha_r)$ as weights because stigma based on race-ethnicity involves identities that are formed at a higher level, where an individual sees herself, for instance, as member of a national majority or minority. This is consistent with evidence from social psychology: perceived affiliation with a racial or ethnic group is associated both with particular beliefs and common behaviors, and the relative sizes of minority groups affect perceptions and actions (Simon and Brown, 1987). We will show later in the paper how these assumptions translate mechanically into estimates.[8] Replacing (6) and (7) into (5), collecting terms and defining $k \equiv k^T + k^I + k^S$, we obtain the probability we wish to estimate:

$$\Pr\left(\pi_{r\ell} = 1\right) = F(k + cX + b\Omega^\ell + \left(J_r^I + J_{ro}^S \alpha_r\right) m_r^\ell + J_{ro}^S \left(1 - \alpha_r\right) \sum_{\rho \neq r} \alpha_\rho^\ell m_\rho^\ell). \tag{8}$$

3 Estimation

The equilibrium participation probability, equation (8), can be estimated using a random cross-section of individuals. In order to control for group-level heterogeneity, we define vectors of group-level controls for race r across locations, Y_r, location ℓ, Y^ℓ, and combination of race and location, Y_r^ℓ. These are collected into vector $Y \equiv \left(Y_r \; Y^\ell \; Y_r^\ell\right)'$. We allow for heterogeneity across race-ethnic groups by estimating equation (8) separately for each group. We conduct our empirical investigation under the canonical linear-in-means model of Manski (1993), i.e. employ a linear probability model:

$$\pi_{ir\ell} = k_r + b_r \Omega^\ell + c_r X_i + d_r Y + J_r^{SI} m_r^\ell + J_o^S m_o^\ell + \varepsilon_{ir\ell}, \tag{9}$$

[8] Technically, the use of weights that are constant across communities (while allowed to vary across race-ethnicities) is needed to obtain separate estimates of stigma from information, as we show below.

where $J_r^{SI} \equiv J_r^I + J_{ro}^S \alpha_r$ is the joint effect of stigma and information from own-group and $m_o^\ell = \sum_{\rho \neq r} \alpha_\rho^\ell m_\rho^\ell$, i.e. the relevant weighted average of out-groups' participation rates. Thus, we are defining $J_o^S \equiv J_{ro}^S (1 - \alpha_r)$ as the stigma effect from other race-ethnic groups. By analogy, we will denote with $J_r^S \equiv J_{ro}^S \alpha_r$ the own-group stigma effect. One would like to estimate the detailed vector of social effects, $\left(J_r^I \; J_r^S \; J_o^S\right)$, but these are not separately identified in model (9). We refer to this as the *conflation problem*[9], the core focus of the current paper.

Of course identification of social effects comes logically first than separate identification, i.e. we must first solve the *reflection problem* (Manski, 1993), which potentially affects any linear model with social interactions. Equilibrium condition (4) implies that the expected participation rate of an individual of race-ethnicity r in community ℓ is equal to the mathematical expectation of the individual participation indicator conditional on the reference group, that is given Y_r^ℓ:

$$m_r^\ell = \mathbb{E}\left(\pi_{ir\ell} | Y_r^\ell\right). \tag{10}$$

This condition, coupled with equation (9), forms a system of simultaneous equations. According to (10), m_r^ℓ depends only on the mean of individual characteristics in the group, $\mathbb{E}\left(X_i | Y_r^\ell\right)$, and Y_r^ℓ, since $\mathbb{E}\left(Y_r | Y_r^\ell\right) = \mathbb{E}\left(Y^\ell | Y_r^\ell\right) = Y_r^\ell$. Suppose, as is the case when one constructs contextual controls from individual data, that the group-level controls, Y_r^ℓ, are the group-level mean of the individual level ones, X_i. That is, $\mathbb{E}\left(X_i | Y_r^\ell\right) = Y_r^\ell$. Then, in absence of a restriction in the form of an individual effect whose average is not a contextual effect, one cannot identify the composite endogenous social effect J_r^{SI} [see Brock and Durlauf (2001)]. We provide a plausible restriction by combining two particular variables in our dataset. First, a variable indicating "whether the respondent has any difficulty learning, remembering, or concentrating, because of a physical, mental, or emotional condition *lasting 6 months or more*." (our italics) This variable reflects both long-lasting impairments and subjective temporary conditions: for example a person may have difficulty concentrating for a few months due to distress following the death of a relative or because of transitory financial problems. Second, a variable indicating "whether respondents have any *lasting* physical or mental health condition that causes difficulty working, limits the amount or type of work they can do, or prevents them from working altogether. This *does not include temporary health conditions*." (our italics). We create a new dummy variable that is equal to 1 if the value of the first variable is 1 and the value of the second is 0. This way we are isolating a temporary individual shock. The reason why this is important when looking for a restriction is that contextual effects, by definition, do not reflect

[9]A term suggested to us by Giacomo Rondina.

temporary subjective states. Contextual effects have to do with the structure of the community; that is, with its objective characteristics. Therefore, while a temporary subjective state of distress might affect an individual's propensity to apply for welfare, the percentage of individuals who report such a subjective state is very unlikely to be the source of any contextual effect.

An additional issue to be addressed is the *selection problem*. Although race is an exogenous trait (which considerably mitigates this problem), individuals in the sample chose to live in a particular area. If residential choices depend on unobservables that also affect the probability of participating in welfare, then the estimated social effects will be affected by selection bias. In our case, the issue is the degree to which neighborhood choice is correlated with welfare participation (benefit shopping). Since welfare arrangements are constant across PUMAs within a state, we believe the problem is a mild one here, except perhaps for a few cases at borders between states with significant differences in welfare benefits [McKinnish (2005)]. We provide later in the paper a test that confirms this intuition: people do not appear to move across PUMAs for reasons related to their decision to work or participate in welfare. Therefore, like other empirical studies in social interactions that use PUMAs as reference groups [e.g. Bertrand et al. (2000) and Luttmer (2005)] we don't need to be concerned with selection as a relevant source of bias.

Separate identification of different social effects is achieved as follows. Equation (9), henceforth referred to as the *primary model*, can also be written as follows:

$$\pi_{ir\ell} = k_r + b_r\Omega^\ell + c_r X_i + d_r Y + J_r^I m_r^\ell + J_{ro}^S \left(\alpha_r m_r^\ell + (1-\alpha_r)\, m_o^\ell\right) + \varepsilon_{ir\ell}, \quad (11)$$

an equation we refer to as the *auxiliary model*. Here total stigma—the last RHS term before the error—captures by construction all social effects that work within *and* across race-ethnic groups in a certain location, but excludes social effects that work exclusively within. This leaves out information sharing, whose effect is captured by the term $J_r^I m_r^\ell$.

Conditional on race, the auxiliary model does not involve new information, because α_r is a constant. Therefore, the corresponding regression models have *exactly* the same errors.[10] In other words, by construction primary and auxiliary models are both "true models." Consequently, we can compare the coefficients of different social effects across them. The two models imply (see the three identities below equation (9)) that an estimator for the stigma effect from own-group r only, J_r^S, is:

[10]This is why we can denote the coefficients on individual and contextual effects with the same symbols in both the primary and the auxiliary model.

$$J_r^S \equiv J_{ro}^S - J_o^S. \tag{12}$$

This is intuitive: since we can compare coefficients across models, to obtain the effect of stigma from race-ethnicity r only, one can subtract from the total stigma effect the portion that does not come from this group. However the two models also imply a second estimator:

$$J_r^S \equiv J_r^{SI} - J_r^I, \tag{13}$$

whose interpretation is again straightforward: own group stigma is equal to total social effects from own-group, net of the effect of information. Of course these two estimators are equivalent. To see this, notice that the marginal effects of participation rates from the primary and auxiliary regression equations, for own-group r and any out-group ρ, are

$$\frac{\partial \Pr(\pi_{ir\ell} = 1)}{\partial m_r^\ell} = J_r^{SI} = J_r^I + \alpha_r J_{ro}^S, \tag{14}$$

$$\frac{\partial \Pr(\pi_{ir\ell} = 1)}{\partial m_\rho^\ell} = \alpha_\rho^\ell J_o^S = (1 - \alpha_r)\, \alpha_\rho^\ell J_{ro}^S. \tag{15}$$

Replace the first of these equations into (12) to get

$$J_r^S = J_r^I + \alpha_r J_{ro}^S - J_r^I = \alpha_r J_{ro}^S. \tag{16}$$

and the second into (13) to get

$$J_r^S = J_{ro}^S - (1 - \alpha_r)\, J_{ro}^S = \alpha_r J_{ro}^S, \tag{17}$$

This provides a way to estimate J_r^S univocally,

$$J_r^S = \alpha_r J_{ro}^S, \tag{18}$$

as well as a useful specification check: if our model is correctly specified, the estimates obtained through (12), (13), and (18), should not be too dissimilar. As we report below, in our sample, they provide very similar answers.

To summarize our discussion, if we denote with x the single excluded individual effect, with superscript j its coefficient and with $\mathbf{i}$ a vector of ones, we can identify social effects separately by estimating the following reduced form equations,[11]

[11]They are obtained in the standard fashion by taking conditional expectations of both sides of

$$\pi_{ir\ell} = \frac{k_r}{1-J_r^{SI}} + \frac{b_r}{1-J_r^{SI}}\Omega^\ell + c_r X_i + c_r^j x_i + \frac{J_r^{SI} c_r + d_r \cdot \mathbf{i}}{1-J_r^{SCI}} Y_r^\ell + \frac{J_r^{SI} c_r^\ell}{1-J_r^{SI}} \mathbb{E}\left(x_i | Y_r^\ell\right) + \frac{J_o^S}{1-J_r^{SI}} \sum_{\rho \neq r} \alpha_\rho^\ell m_\rho^\ell + \varepsilon_{ir\ell}, \quad (19)$$

$$\pi_{ir\ell} = \frac{k_r}{1-J_r^I} + \frac{b_r}{1-J_r^I}\Omega^\ell + c_r X_i + c_r^j x_i + \frac{J_r^I c_r + d_r \cdot \mathbf{i}}{1-J_r^I} Y_r^\ell + \frac{J_r^I c_r^\ell}{1-J_r^I} \mathbb{E}\left(x_i | Y_r^\ell\right) + \frac{J_{ro}^S}{1-J_r^I}\left(\alpha_r m_r^\ell + (1-\alpha_r) \sum_{\rho \neq r} \alpha_\rho^\ell m_\rho^\ell\right) + \varepsilon_{ir\ell}, \quad (20)$$

and then recover the social interactions coefficients and their standard errors using the delta method. Of course we cannot separately identify the coefficients on the composite variable $Y \equiv \left(Y_r \; Y^\ell \; Y_r^\ell\right)'$, only their sum, $d_r \cdot \mathbf{i}$, is identified. Also, the coefficients on the individual controls have no obvious interpretation because we have used these to form a linear prediction of the benefits an individual is entitled to. This is not important, because our goal is to identify separately stigma and information effects for different race-ethnic groups, that is the vector $\left(J_r^I \; J_r^S \; J_o^S\right)$. Overall, this strategy isolates information, that is non-preference-based social effects, from other effects that operate through preferences. Notice that stability requires $\left(J_r^{SI}, J_r^I, J_r^S, J_o^S\right) < (1,1,1,1)$. Our theoretical model predicts that both J_r^I, the information effect and J_r^S and J_o^S, the stigma effects from own- and out-group, are positive.

What is the social multiplier, i.e. the cumulative effect of an exogenous shock, implicit in this framework? Suppose that the individual probability of participating in welfare for a certain race at the PUMA level decreases exogenously by 1 percentage point. Absence any cross-group effect, the equilibrium cumulative effect would simply be $\left(1 - J_r^{SI}\right)^{-1}$. However, in the presence of cross-group stigma, the other race-ethnic groups are also affected by the shock, which generates further feedback effects. From equation (9) we can compute the initial reaction to the unit increase: this is equal to $J_r^{SI} + J_o^S \sum_{\rho \neq r} \alpha_\rho^\ell (\partial m_\rho^\ell / \partial m_r^\ell)$. The social multiplier implied by our model is the reciprocal of one minus such a quantity, which can be written as follows,

equations (9) and (11), using as contextual effects the means of all non-excluded individual effects, solving for m_r^ℓ, and replacing back.

$$\left(1 - J_r^{SI} - J_o^S \alpha_r^\ell m_r^\ell \sum_{\rho \neq r} \alpha_\rho^\ell J_{o(\rho)}^S\right)^{-1}, \tag{21}$$

since the response of race-ethnicity ρ's participation rate to group r's, $\partial m_\rho^\ell / \partial m_r^\ell$, is simply $J_{o(\rho)}^S \alpha_r^\ell m_r^\ell$, where $J_{o(\rho)}^S$ is the cross-group coefficient for race-ethnicity ρ. The multiplier in (21) is of course larger than $\left(1 - J_r^{SI}\right)^{-1}$. The $1 - J_r^{SI}$ component should be easily recognizable as the own-group effect. The final term is the portion of the shock that operates through out-groups. Therefore, the social multiplier generated by our model is special in two respects: (1) it is group-specific, so that in general a given policy will impact race-ethnic groups differently; (2) it depends on the initial participation rate, so that the effect of a certain policy depends on initial conditions. We will later illustrate this fact with a numerical simulation based on our estimates.

4 Dataset

We use data from the 2000 Census 5% PUMS (Public Use Microdata Sample), drawn from the IPUMS website at the University of Minnesota. Reference groups are defined as race-ethnic groups according to the US Census categories at the PUMA level, the lowest level of aggregation available in PUMS. The national weights we employ are computed from the 2000 National Census: 0.69 for White Nonhispanic, 0.13 for Hispanic of all races, 0.12 for Black Nonhispanic, 0.04 for Asian, 0.01 for Natives. The remaining race-ethnicities, Pacific Islanders and Others, have negligible weights and are not considered.[12] For estimation, although we consider all groups for the purpose of defining out-groups, we will focus on the three largest race-ethnic groups, at the PUMA level: Black Nonhispanic, Hispanic of any race, and White Nonhispanic.

The dataset is constructed following Bertrand *et al.* (2000) closely. After excluding the institutional population, we restrict the sample to women between 15 and 55 years old. This captures only the working age population and avoids overlap with Social Security payments to those in older demographic brackets. It also acknowledges the fact that welfare policy is targeted principally at families with children, a demographic that almost universally includes women. Own-group effects are calculated as the sample average of the welfare participation variable of individuals of the same race-ethnicity within a PUMA. Outgroups are the remainder of the population in the given PUMA. Contextual variables are estimated using

[12] The remaining part to 100% consists of individuals who indicate more than one race, for instance both White Hispanic and Black. We do not consider these either.

sample averages of individual variables, by race at the PUMA level.[13] We also included in the dataset the number of social workers in the state of residence per thousand citizens, as provided by the Bureau of Labor Statistics, as well as the minimum wage in the state of residence at the time our data were collected. The number of social workers proxies for the theoretical variable Ω.[14] Our final sample contains 462,259 Blacks, 479,608 Hispanic, 2,766,673 White nonhispanic, as well as 265,166 individuals of other race-ethnicities, which are included in the computation of welfare participation rates. Thus, this study is based on a sample of about four million individuals.

Table 2 lists the variables we use. Our indicator of welfare usage is a dummy variable that is set equal to one if an individual receives transfers in the form of public assistance income, excluding SSI (Supplemental Security Income), Earned Income Tax Credit, as well as assistance from private charities.[15] As shown, we use a simple set of individual controls that appear to be relevant for the problem at hand. The inclusion of the average of these individual effects—in addition to the number of social workers and minimum wage—as contextual controls allows us to capture most local effects. We also use squares of all these to obtain more flexible estimates. This makes a total of 110 regressors.

Table 3 reports descriptive statistics. These show that the welfare participation rates of Black, Hispanic, and White individuals in the sample are, respectively, 7.3%, 4.9% and 1.5%. Not surprisingly, individuals on welfare tend to be younger (except for Hispanics), less educated, poorer, with more kids. There also appears to be a very high concentration of individuals out of the labor force and single mothers, with lower rates of fluency in English (except for Blacks). Also notice that the availability of social workers is higher in places where Whites live (1.98 per thousand people), compared to places where Blacks (1.84) and Hispanics (1.71) live.

[13]In order to assess how good this approximation is, note that of the four million individuals in the sample, about 85,000, or roughly 2%, have fewer than 100 neighbors. When estimating our main model without these individuals (results are available from the authors upon request) the estimated coefficients vary only marginally. Because of this, we work with the full sample because it is not clear what the appropriate cutoff should be, i.e. 100 rather than 1000 or 10 neighbors in the sample.

[14]We use the 2005 BLS estimate, under the assumption that the number of social workers per thousand citizens did not change dramatically since 2000. More specifically, we used the sum of Social and Human Service Assistants (who provide support for families, assisting them identifying and obtaining available benefits and social and community services) and Child, Family, and School Social Workers (who assist children, their families, and notably single parents).

[15]Note that some transfers, like food stamps, are effectively in-kind and may not be reported by individuals as welfare assistance.

5 Results and checks

We estimated models (19)-(20) by Ordinary Least Squares (OLS), and recovered the structural coefficients and standard errors using the delta method. Table 4 contains our key results, namely the estimated social interactions coefficients[16]. This table shows an interesting pattern. While the total social effect from own race-ethnicity, J_r^{SI}, is similar across the three groups (with a slightly larger coefficient for Blacks, row one), there are clear differences in its composition: information, J_r^I, rather than stigma, J_r^S, is the predominant own-group effect for Blacks and Hispanics (row three), while Whites, for whom the effect of information is statistically indistinguishable from zero, are subject to a strong stigma effect from other Whites (row five) relative to minorities—an order of magnitude larger. Cross-group social effects (row two) are not statistically different across the three main ethnicities we consider, but while minorities are subject to a strong stigma effect from other groups relative to own-group stigma, the opposite holds for Whites. To relate this to the race and ethnicity laden discussion of welfare participation, our results suggest that Blacks' and Hispanics' decision to take up welfare is principally a function of socioeconomic features, group-level information sharing, and the stigmatization effects of *other* races and/or ethnicities. Whites' participation decision, on the other hand, is mainly a function of own-group stigma among all the possible social effects we considered. We find these asymmetries to be noteworthy. The last two rows of Table 4 report results of a simple specification check on our separation strategy. Namely, we computed the own-group stigma effect that is implied by equations (12) and (13), to be compared with our estimate using equation (18). There is some discrepancy, which is not surprising, but one of the central patterns we uncover is quite robust: own-group stigma is very important for Whites, but negligible for Blacks and Hispanics.

What is the effect of α_r in equations (17)-(16) on these estimates? We gain intuition into the mechanics of the model by re-estimating social effects as a function of α_r for each group, keeping the sum of weights constant. We do this exercise over the range where the distribution of population shares concentrates. Figure 1 illustrates. The solid line is the kernel density estimate (left scale) of the population share of a given race-ethnic group across states. The group share, i.e. α_r in our model, is reported on the horizontal axis. We report on the same graph (right scale) the social effect we would estimate using a particular level of α_r. Our baseline estimates are located by a dashed box. For the Black and Hispanic groups, our results are substantially unaffected by a perturbation of the weight, while they seem to vary faster with α_r for Whites–a scale effect due to a large α_r and a low participa-

[16]Full regression output is available from the authors upon request.

tion rate for this group. The general pattern is that as α_r increases, the importance of stigma also increases and the importance of information decreases. This is tautological: as the relative importance of stigma from own-group increases, the stigma effect must be larger, and consequently—given the total own-group effect—the importance of information must decrease. Equation (5) makes this point clear. Overall, over the relevant range our results seem robust to perturbations of the national weight we use.

In order to assess the quantitative implications of the social effects we estimate, suppose there is a uniform exogenous decrease of 5% in the welfare rolls across race-ethnic groups, with initial participation rates given by the sample means. Table 5 shows the effect of such a shock on the equilibrium participation rates, using the "overall" social multiplier defined by equation (21). The implied cumulative effect is a reduction of a quarter in the participation rate for Blacks (equivalent to 1.78 percentage points), one seventh in the participation rate of Hispanic (0.71 percentage points) and one fourteenth in the participation rate of Whites (0.13 percentage points). These might be regarded as large numbers – especially for Blacks. Yet, we believe this exercise makes a strong methodological point. In particular, it turns out that the contribution of information to such reduction—given by the social multiplier in the case in which information is the only relevant social effect—is very large for Blacks and Hispanics (almost 90%), but slightly more than a third for Whites. The reduction in the participation rate of Whites is thus driven by own-group stigma, with stigma from others groups practically negligible. On the other hand, the reduction in the participation rate of minorities is driven by information. The large difference in the social multiplier between Blacks and Hispanic is due to the larger total social effect from own race-ethnicity for the former.[17]

Tables 6a-6c report estimates of the same social effects by race-ethnic group and by education and income classes. We focus on low education (high school dropouts and high school graduates, respectively) and low income (income at or below the bottom 2 quintiles of the income distribution in our sample), where welfare participation is more concentrated. These tables show further interesting patterns. First, in agreement with intuition, information is more important for low-educated people relative to the average, i.e. the coefficients increase with respect to those in Table 4. Second, and related to the first point, there are virtually no differences in the predominant role of information sharing for the very low educated, i.e. high school dropouts, across race-ethnicities, while Table 4 reported marked differences for the population at large. Third, for Blacks the effect of social interactions is essentially invariant across the three dimensions we consider, suggesting, consistent

[17] The apparently small difference (0.1) is magnified by multiplier effects: $(1 - 0.7)^{-1} = 3.33$, while $(1 - 0.8)^{-1} = 5$.

with Social Identity Theory, some effect of racial identity for this group.

Table 7 reports two pieces of evidence to support the claim that our results are likely not impacted by selection into PUMAs. In column 1, we regress the move decision on the panel of covariates used in the remainder of the study and the welfare participation decision. The very large and negative coefficient shows that, after controlling for a variety of local and individual effects, there is a negative relationship between welfare and mobility. That is, individual on welfare are much less likely to move than others. Column 2 changes the focus slightly. We first restrict the sample only to movers and then assign a value of one to movers that moved beyond a state line. Of course, since welfare rules are state-specific, benefit shopping is only effective with a cross-border move. We regress our new variable on the same independent variables. The coefficient on the welfare variable is now indistinguishable from zero. Jointly, it suggests that welfare recipients are less likely to have moved than the rest of the population, and, if they moved are no more likely to have moved across state lines than within a state. As such, we are confident that selection, if present, is sufficiently small that it will not impact inference.

6 Discussion and conclusions

In this paper we have argued that when trying to estimate the effect of social interactions on economic behavior, it may be important to explicitly address the fact that different social effects, with different policy implications, are possibly at work. We have illustrated a simple way to separately identify different effects, with an application to welfare participation in the US. We have jointly estimated two social effects. The first is the effect of the welfare participation decisions of one's own race and ethnicity on individual decisions and the second is the joint effect of these decisions and those of different races in the same local (PUMA) area. We find that the own-group effects are more salient overall, with some degree of instructive heterogeneity. From this starting point, we argue that, using labels from social psychology, [Campbell and Fairey (1989)] we can labeled such effects 'information' and 'stigma.'

The result that information is the predominant social effect in welfare participation is consistent with the findings of Heckman and Smith (2003) as well as Aizer (2007) on the relevance of informational barriers in determining program participation rates, as well as with the experimental evidence reported in Daponte *et al.* (1999). On the other hand, our findings are apparently at odds with those of Aizer and Currie (2004) about network effects in the use of publicly funded maternity services, based on panel data on first and second pregnancies of a sample of women in California. Their main test of the information hypothesis is based on the argument that if information is to be the predominant social effect then the magnitude of total social effects must be smaller for second deliveries, which is not the case in their dataset. We believe this result does not necessarily contrast with ours, for two reasons. First, since in their sample first and second deliveries are on average three years apart, it may well be that information relative to first delivery is obsolete for many women in the sample. Second, and more importantly, our data are close to a major welfare reform which may have made information particularly salient.

It is worth noting that the combination of different social effects is present in other contexts. We mention three examples. One, consider students in a high school setting in which information sharing through collective learning can contribute to improved test scores. Many high school environments also include (often negative) stigma associated with good test performance [Akerlof and Kranton (2002)]. Two, access to medical care in poor communities is often a patchwork of public and private providers, a system that takes effort and understanding to navigate. However, it's been noted that access to care for individuals with HIV, depression, obesity (and other illnesses) is associated with a social stigma [Herek *et al.* (2002); Eisenberg *et al.* (2007)]. Three, much controversy surrounded the 2005 bankruptcy reform act. In particular, a debate emerged over the motivations for declaring bankruptcy that again split down information and stigmatization lines. Cohen-Cole and Duygan-Bump (2008) use a similar methodology as we have to evaluate this question. We don't opine here on the correct structuring of investigations into these issues, but mention them to illustrate that the welfare case is not unique in needing evaluation of multiple drivers of social interactions. We argue that this implies a need for methods of distinguishing the nature and composition of the effects in each context.

Regardless of the labeling convention used, we think our investigation offers important insights. In particular, it shows that different social effects may be at work in welfare participation decisions, and that they operate differently across race-ethnic groups. This in turn, is important to understand the working of welfare and to evaluate alternative policies.

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Table 1. Social Expenditure in OECD countries

	1980	**1985**	**1990**	**1995**	**2000**	**2003**
Australia	10.9	13.0	14.1	17.1	17.9	17.9
Belgium	23.5	26.1	25.0	26.4	25.3	26.5
Canada	14.1	17.3	18.4	19.2	16.7	17.3
Denmark	25.2	24.2	25.5	28.9	25.8	27.6
Finland	18.4	22.8	24.5	27.4	21.3	22.5
France	20.8	25.8	25.3	28.3	27.6	28.7
Germany	23.0	23.6	22.5	26.6	26.3	27.3
Greece	11.5	17.9	18.6	19.3	21.3	21.3
Ireland	16.8	21.8	15.5	16.3	13.6	15.9
Italy	18.0	20.8	19.9	19.8	23.2	24.2
Japan	10.3	11.2	11.2	13.9	16.1	17.7
Luxembourg	23.6	23.1	21.9	23.8	20.4	22.2
Netherlands	24.1	24.2	24.4	22.8	19.3	20.7
New Zealand	17.1	18.0	21.8	19.0	19.1	18.0
Portugal	10.8	11.0	13.7	18.1	20.2	23.5
Spain	15.5	17.8	20.0	21.5	20.4	20.3
Sweden	28.6	29.7	30.5	32.5	28.8	31.3
Switzerland	13.9	14.8	13.5	17.5	18.0	20.5
United Kingdom	16.6	19.6	17.2	20.4	19.1	20.6
United States	13.3	12.9	13.4	15.4	14.6	16.2
OECD - Total	**15.9**	**17.6**	**17.9**	**19.9**	**19.4**	**20.7**

Note. This table reports total (in cash and in kind) expenditure of general government for social policy (health, pensions, unemployment, housing, family, disability, etc.) as a percentage of GDP. Source: OECD. As of August 2008, the latest available year in the dataset is 2003.

Table 2. Variables used

Variable	Description
welfare:	Welfare participation indicator
age:	Age of individual
childpresent:	Children present
nchild:	Number of children present
nfamilies:	Number of families in household
hsdropout:	Educational attainment: high school droupout
hsgrad:	Educational attainment: high school graduate
collegemor:	Educational attainment: more than college
singlemother:	Single mother
marriedsabsent:	Married, spouse absent
widowed:	Widowed
divorced:	Divorced
separated:	Seperated
nevermarried:	Never Married
poorenglish:	Poor English fluency
unempl:	Unemployed
nolabforce:	Not in labor force
nophone:	No phones present in household
income:	Gross household income (including welfare)
poverty:	Poverty indicator (income in % of poverty line)
workdisabl:	Work disability
socworkers	Social Workers per 1,000 citizens
statewage	State minimum wage
temphealth	Temporary negative health condition

Note. We use as controls these variables, their PUMA-level averages when appropriate (contextual effects) as well as the squares of all these. This makes a total of 110 controls.

Table 3. Means of controls by race-ethnicity and welfare status

	Black		Hispanic		White		All	
	Welfare	No Welf.	Welfare	No Welf.	Welfare	No Welf.	Welfare	No Welf.
Variable	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
age	33.35	34.52	33.57	32.36	34.27	36.34	33.85	35.43
childpresent	0.74	0.50	0.77	0.55	0.67	0.48	0.72	0.49
nchild	1.76	0.95	1.96	1.18	1.33	0.89	1.67	0.94
nfamilies	1.20	1.18	1.32	1.30	1.32	1.17	1.28	1.19
hsdropout	0.41	0.24	0.63	0.46	0.31	0.14	0.44	0.20
hsgrad	0.34	0.27	0.22	0.22	0.35	0.24	0.31	0.24
somecollege	0.23	0.34	0.13	0.23	0.27	0.33	0.21	0.31
collegemore	0.02	0.16	0.02	0.10	0.07	0.29	0.04	0.25
singlemother	0.64	0.27	0.51	0.13	0.46	0.09	0.53	0.12
marriedsabend	0.04	0.03	0.05	0.04	0.03	0.01	0.04	0.02
widowed	0.03	0.02	0.03	0.01	0.02	0.01	0.03	0.01
divorced	0.12	0.13	0.14	0.08	0.28	0.12	0.18	0.11
separated	0.10	0.06	0.15	0.04	0.10	0.02	0.11	0.03
nevermarried	0.63	0.47	0.39	0.34	0.34	0.28	0.45	0.31
poorenglish	0.01	0.01	0.31	0.26	0.02	0.01	0.11	0.05
unempl	0.18	0.06	0.13	0.06	0.10	0.03	0.13	0.04
nolabforce	0.48	0.27	0.57	0.40	0.48	0.24	0.51	0.27
nophone	0.11	0.03	0.09	0.03	0.07	0.01	0.09	0.02
income	18,113	46,190	20,342	49,010	26,070	74,973	21,931	67,356
poverty	114.47	264.97	116.22	239.17	159.01	364.19	132.14	330.88
workdisable	0.17	0.15	0.16	0.13	0.22	0.08	0.18	0.10
socworkers	1.89	1.84	1.91	1.70	2.01	1.98	1.93	1.91
statewage	5.27	5.24	5.46	5.41	5.40	5.32	5.38	5.33
temphealth	0.06	0.02	0.06	0.02	0.08	0.01	0.07	0.02

	Black	Hispanic	White	All
Welfare	0.073	0.049	0.015	0.029

Table 4. Estimates of Endogenous Social Effects

Social effect	Coeff.	Black	Hispanic	White
Stigma and Information from own group	J_r^{SI}	0.82***	0.70***	0.72***
		(0.03)	(0.07)	(0.06)
Stigma from other groups	J_o^S	0.12***	0.15***	0.09***
		(0.03)	(0.04)	(0.02)
Information (own group)	J_r^I	0.80***	0.66***	0.29
		(0.04)	(0.08)	(0.23)
Stigma from own and other groups	J_{ro}^S	0.21***	0.27***	0.65***
		(0.05)	(0.07)	(0.22)
Stigma from own group	J_r^S	0.03***	0.03***	0.45***
		(0.01)	(0.01)	(0.15)

*: significant at 5% – ***: significant at 1% or better

Specification Check:

J_r^S implied by equation (18)		0.03	0.03	0.45
J_r^S impled by equation (13)		0.02	0.04	0.43
J_r^S impled by equation (12)		0.09	0.12	0.56

Note. This table reports estimates of the endogenous social effects considered in our model. Reduced-form coefficients are obtained by applying OLS to equations (19) and (20). Structural coefficients and their standard errors are obtained using the delta method. The dependent variable is the welfare participation indicator. Individual controls are all the individual-level variables listed in Table 1, as well as their squares. Contextual controls are the sample means (at the level of PUMA and combination of PUMA and race-ethnicity) of the varibles listed in Table 1 – except for temphealth which is our exclusion restriction – as well as their squares. This makes a total of 110 (one hundred and ten) controls. Full regression output is available from the authors upon request.

Figure 1. Social effects as a function of α_r
Top: Black. Middle: Hispanic. Bottom: White.

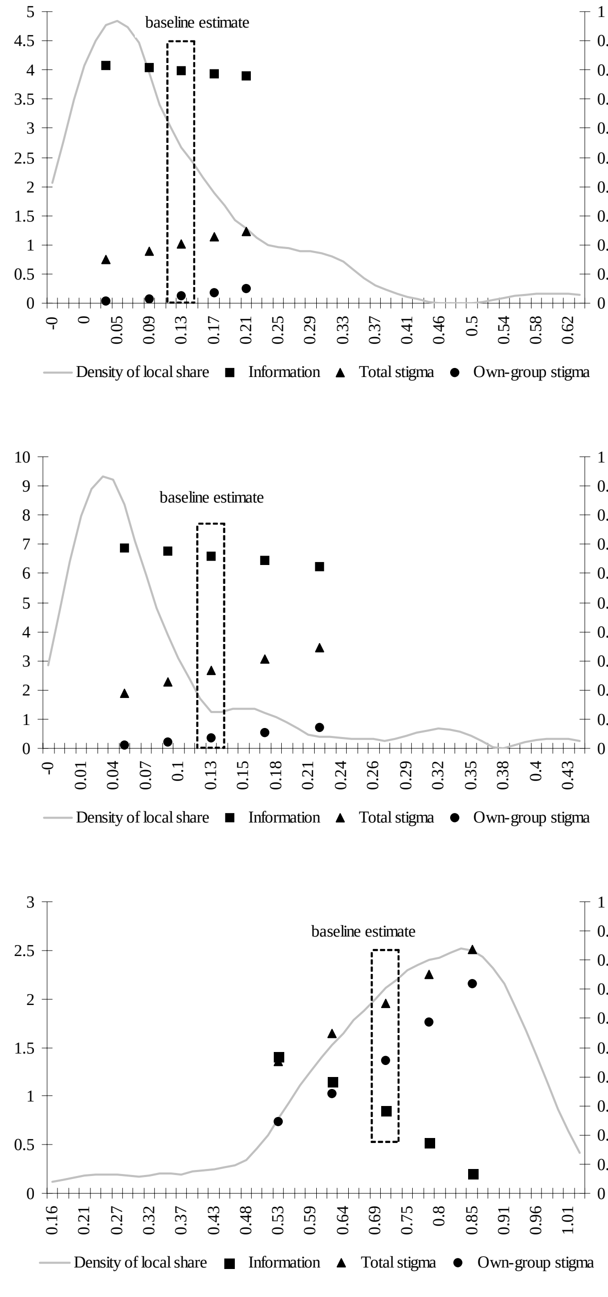

Table 5. Effect of a 5% uniform reduction in participation

	Black	Hispanic	White
Initial participation rate	*7.10%*	*4.80%*	*1.80%*
Initial reduction in %	5%	5%	5%
Reduction in % points	0.36	0.24	0.09
Overall Social Multiplier	5.59	3.35	3.60
Multiplier of information	5.00	2.94	1.41
Total effect in % points	1.78	0.71	0.13
Final reduction in %	25.00%	14.71%	7.04%
Final participation rate	*5.32%*	*4.09%*	*1.67%*
Contribution of information	89%	88%	39%

Table 6a. Social effects at low levels of education and income

	Black		
Coeff.	High School dropout	High School degree	Below 2nd income quintile
J_r^{SI}	0.89***	0.84***	0.85***
	(0.03)	(0.06)	(0.04)
J_o^S	0.11***	0.13***	0.13***
	(0.03)	(0.05)	(0.04)
J_r^I	0.88***	0.81***	0.82***
	(0.03)	(0.08)	(0.05)
J_{ro}^S	0.17***	0.24*	0.23***
	(0.05)	(0.10)	(0.07)
J_r^S	0.02***	0.03*	0.03***
	(0.01)	(0.01)	(0.01)

*: significant at 5% – ***: significant at 1% or better

Table 6b. Social effects at low levels of education and income

	Hispanic		
Coeff.	High School dropout	High School degree	Below 2nd income quintile
J_r^{SI}	0.81***	0.68***	0.77***
	(0.05)	(0.13)	(0.07)
J_o^S	0.10***	0.18*	0.15***
	(0.03)	(0.09)	(0.05)
J_r^I	0.79***	0.64***	0.74***
	(0.07)	(0.16)	(0.08)
J_{ro}^S	0.19***	0.32*	0.27***
	(0.06)	(0.16)	(0.09)
J_r^S	0.02***	0.04*	0.03***
	(0.01)	(0.02)	(0.01)

*: significant at 5% – ***: significant at 1% or better

Table 6c. Social effects at low levels of education and income

	White		
Coeff.	High School dropout	High School degree	Below 2nd income quintile
J_r^{SI}	0.88***	0.70***	0.80***
	(0.03)	(0.11)	(0.05)
J_o^S	0.08***	0.13*	0.11***
	(0.03)	(0.06)	(0.03)
J_r^I	0.80***	0.10	0.54***
	(0.08)	(0.91)	(0.20)
J_{ro}^S	0.34***	1.10	0.76*
	(0.13)	(1.12)	(0.33)
J_r^S	0.24***	0.76	0.52*
	(0.09)	(0.77)	(0.23)

*: significant at 5% – ***: significant at 1% or better

Table 7. Selection Test

	(1)	(2)
welfare	-0.0802***	-0.00241
	(0.0023)	(0.0018)
Constant	1.074	0.314
Observations	2,695,816	1,337,429

*: significant at 5% – ***: significant at 1% or better

Note. In column 1, the dependent variable is the move decision. Column 2 assigns a value of one to movers that moved beyond a state line and zero to individuals that moved within a state. Non-movers are excluded from column 2. All covariates used in study are include. Results are available on request.