Stigma and Information in Welfare Participation

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Abstract

In this paper we try to identify social interactions in welfare participation, and to separate stigma and information effects, which have different policy implications. Using US census data, we find that social interactions affect welfare participation decisions, in line with previous empirical studies. This can explain why participation rates are lower than expected in the US. However, we also argue that information, i.e. the constraints side, is more important than stigma, i.e. the preferences side. We also find differences across races/ethnicities. White Americans appear to be stigmatized more by other White Americans than by other races. The opposite holds for the two minorities we consider, Black and Hispanic Americans. Our findings suggest that the presence of different "welfare cultures" is more likely due to information sharing than different attitudes toward work. We perform robustness tests to address problems of unobserved group effects, self-selection, and alternative identifying restrictions, and do not find substantially different results.

JEL Classification Codes: I30, Z13.
Keywords: social interactions, neighborhood effects, welfare stigma.

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1 Introduction

Many social scientists and commentators believe that welfare participation decisions depend not only on individual risk factors such as being poorly educated or a being a single young mother, but also on the social context, often epitomized with the expression "welfare culture". The idea is that interacting with many people on welfare may increase the likelihood of becoming welfare dependent. There are many reasons why it may be so, but two have received special attention in the literature. One is the information channel: people may share information on eligibility, application procedures, bureaucratic details and the like with acquaintances. The second is the stigma channel: being surrounded by people on welfare may decrease the embarrassment of receiving public transfer, as "everybody does it". It is this concept that has underlain much of the welfare reform literature (see for example Mead 1986). Social scientists of various disciplines have noticed the phenomena that there are geographic concentrations of people, often minorities, that participate in welfare at a rate greater than would be predicted by the surrounding socioeconomic conditions alone. When making policy decisions regarding welfare reform, the nature of the participation decision is essential. To address this issue, our purpose in this paper is to detect empirically the possible effect of social interactions on welfare participation decisions, using US data, and to identify separately the contribution of information and stigma. Our work has a methodological and a substantive motivation.

The substantive motivation is a presumption that social effects may help answer puzzling features of welfare programs, including those mentioned above. For instance, a remarkable feature of the welfare system in the United States is that a significant fraction of eligible individuals do not participate. According to the estimates of the US Department of Health and Human Services (2005), less than 50% of eligible households applied for Temporary Aid to Needy Families (TANF) and Food Stamps in 2001 and 2002.[1] This followed a downward trend that began at mid 1990s, as depicted in figure 1 below. Why do so many households fail to take advantage of programs that are clearly in their economic interest, i.e. do not locate on the boundary of the budget constraint? Welfare benefits can amount to several thousand dollars, and one wonders why so much money is "left on the table". As

[1] Zedlewski and Brauner (1999) and Zedlewski and Gruber (2001), as well as the General Accounting Office (1999) have documented that a large majority of welfare "leavers" that continued to be eligible for food stamps, did not continue to participate.

the figure reveals, a sharp downturn occurred along with the 1996 welfare reforms, which introduced minimum work requirements and other restrictions. There are a host of reasons why this decline may have taken place (see Danielson and Klerman 2004 for a thorough review). Among them one could plausibly argue that these changes induced many individuals to reveal the value of non-market activities, such as childrearing, undertaken by single mothers on welfare. However, the parallel decline in the take-up rate for Food Stamps, which have less stringent work requirements, suggests something else may cause a generalized decline in welfare participation by eligible households.

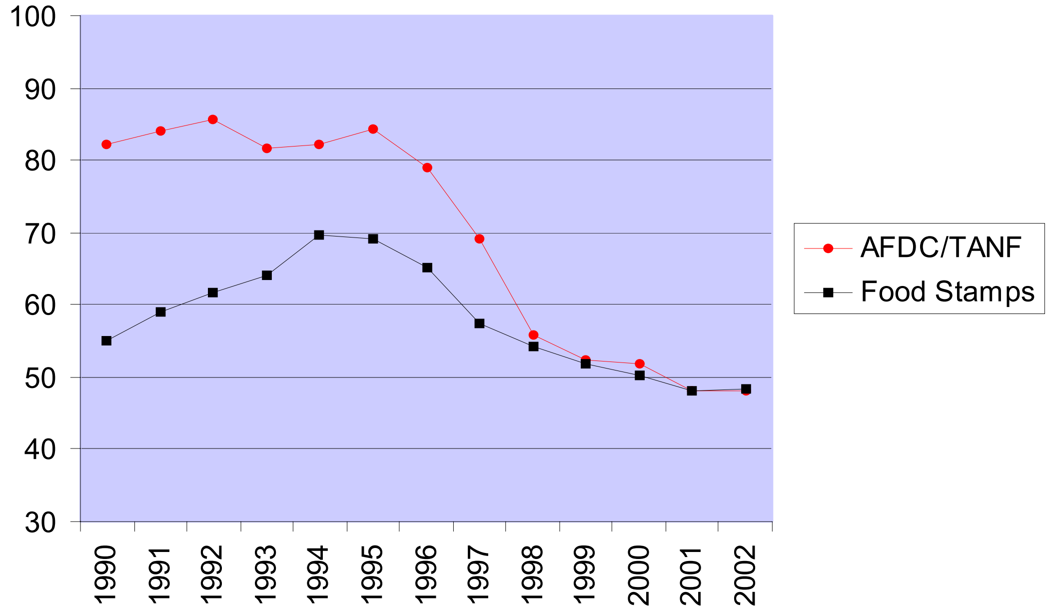

Fig 1. "Take-up" rates for AFDC/TANF and Food Stamps. Source: US DHHS (year 1991 for AFDC is missing and interpolated by simple average)

In a pioneering paper addressing the issue of eligible non-participants to welfare programs, Moffitt (1983) provided an explanation constructing and estimating a model of welfare stigma.[2] Moffitt defined welfare stigma

[2] Other work on the effect of social stigma on welfare use from this time period includes (Rank, 1994; Nichols-Casebolt, 1986; Katz, 1989; Kelso, 1994, Murray 1984)

in an introspective sense, as a feeling of lack of self-respect and negative self-characterization: whenever an individual earns welfare income, he or she suffers disutility from welfare participation *per se*. Moffitt's estimates of such disutility are large, thus providing an explanation of the apparent paradox of non-optimizing individuals. However this argument cannot be used to interpret the time series in figure 1, unless one is willing to accept an explanation of the kind "a parameter in the utility function changed over time". In a more recent paper, Lindbeck et al. (1999) define stigma in a social sense, as the punishment for the violation of a social norm of the kind "everybody should live off his own work". The intensity of such norms are assumed to be endogenous, namely they decrease with the fraction of the population that participates in welfare. A possible reason is that it is less embarrassing to live on public transfers when other individuals in one's "social window", or reference group, do likewise. The social interpretation of stigma is consistent with the declining pattern of take-up rates, because it implies a social multiplier. This is defined as the ratio between the cumulative and the initial responses to a shock. For instance the 1996 welfare reform may have initially driven a number of families out of the former AFDC program, thus making welfare dependency more embarrassing for those who remained, subsequently driving some of them out of public assistance, reinforcing the embarrassment of those remaining, and so on in a cumulative way until a new equilibrium participation rate is reached.

The methodological motivation is that some features of existing empirical analyses of social interactions in welfare participation are somewhat unsatisfactory. To our knowledge, the best attempt in this field is Bertrand et al. (2000), who assume reference groups are defined by language spoken at home. They find that the probability of participating in welfare programs for women of working age increases with the fraction of welfare-recipients in one's linguistic group either at the PUMA[3] or MSA[4] geographic level. However, this social effect may be due to a multiplicity of reasons, as Bertrand et al. (2000) recognize. What they identify may be the effect of stigma,

[3] A PUMA (Public Use Microdata Area) is an area defined by the US Census Bureau, with a minimum population of 100,000. The definition criteria aim at drawing meaningful boundaries from an economic and statistical viewpoint.

[4] A MSA (Metropolital Statistical Area) is defined by the Census Bureau as "a core area containing a substantial population nucleus, together with adjacent communities having a high degree of social and economic integration with that core". It can comprise one or more entire counties.

information sharing, or any other effect that is correlated with the fraction of women on welfare in one's reference group or, more likely, the compound effect of all these. These effects have different implications for welfare policy: the picture is very different if the decline in take-up rates is the effect of being stigmatized when receiving public assistance rather than reduced information in the face of an increasingly complex welfare legislation. In the first case there's little a government can do to affect take-up rates without simply limiting access across the board. Therefore, estimates of a compound social effect is of limited use without an idea of its composition.

Our contribution is the first attempt, to our knowledge, to identify separately different social effects in individual behavior. Our strategy goes as follows. First we focus on stigma and information *within* and *across* racial and/or ethnic groups[5] at the PUMA level, our definition of reference groups[6]: the more individuals are on welfare across race or ethnic groups in a PUMA, the less embarrassing it is to receive public transfers (lower stigma) and the more likely it is to be connected with someone within one's group who can provide useful information on welfare eligibility, application procedures and other administrative details. Both effects predict a positive relationship between the individual probability of participating in welfare and the participation rate in the reference group.

We achieve identification applying the techniques developed by Brock and Durlauf (2001) for the empirical analysis of social interactions. This allows us to get rid of econometric problems - notably the so called reflection problem - we believe may affect previous empirical studies. Specifically, we explicitly address the endogeneity of mean behavior across race groups within PUMAs and estimate reduced rather than structural forms for each race. Then we rely on an exclusion restriction - an individual effect whose average is not a contextual effect - to recover the structural parameters. We test our preferred restriction against alternative ones, showing that our estimates are robust to alternative choices. Once identification is secured, separation is achieved arguing that different reference groups are associated with different social effects. In particular, we assume that one's race group is a source of

[5] Of course other kind of social effects may be at work, but focusing on two of them is enough to make at least a methodological point. However, since stigma and information receive a lot of attention in the welfare literature, we think we are also making a substantive point.

[6] We focus on PUMAs rather than MSAs because they are generally overlapping in metro areas, while the former includes non metro areas as well.

stigma and information, while other race groups are a source of stigma only. The basis for this argument is a political economy view of welfare stigma, according to which preferences for redistribution are affected by the number of welfare recipients of one's own race in one's community (Luttmer, 2001, Alesina and Glaeser, 2004).

Interpreting our results, we find substantial heterogeneity across races in terms of which social effects are relevant for welfare participation. While we find that information is more important than stigma for the races and ethnic groups in our sample, stigma from own group (race or ethnicity) matters for White Americans but is negligible for Black and Hispanic Americans. For Black and Hispanic Americans, we find that stigma from their own group is of negligible importance, but stigma from other groups is relevant. Based on these results, we conclude that the decline in take-up rates may be due to the existence of a social multiplier, which is complex in the sense that results from a mixture of mechanisms that differ across races. Such complexity is of obvious importance for welfare policy.

The remainder of the paper is organized as follows. In the next section we build a simple theoretical model of welfare participation in presence of different kind of social interactions, which leads to the econometric specification in section 3. In section 4 we describe and summarize our dataset. In section 5 we presents the results and perform several tests. Section 6 concludes.

2 A simple theoretical framework

Consider the following one-period problem[7]. Welfare participation is a binary variable, π. An individual must decide whether to work and live on wages, in which case he does not participate in welfare ($\pi = 0$) and earns wage w, or not work and live on welfare ($\pi = 1$), in which case he receives transfer T, and pays a participation cost[8], denoted by C. Let's introduce social interactions in this framework. Imagine the economy has a social structure, i.e. is made of *reference groups*. One's reference group is denoted by g, and others' are collectively denoted by o, or *outer group*. We consider two

[7]Although welfare participation is best analyzed as a dynamic problem, a simple static model is enough to interpret our empirical results, which are based on cross-section data.

[8]The participation cost is not necessarily an out-of-pocket cost: it is a simple way to capture the role of information too. For instance being unaware of welfare eligibility is tantamount to an infinite participation cost in the context of a choice model.

kind of social interactions, i.e. two ways individuals affect each other in this economy: information sharing and stigma. We assume individuals share information about welfare within reference groups, but not across. This can be modeled assuming that the participation cost C is a decreasing function of the expected welfare participation rate of individuals who are members of one's reference group, m_g. This captures the idea that the more people in one's group are expected to receive welfare transfers, the more likely it is be connected with one of them, and so to receive information that reduces the participation cost. We also assume individuals suffer welfare stigma within and across groups, i.e. from reference and outer groups. This is a consequence of what Luttmer (2001) calls *racial group loyalty*, i.e. individual support for welfare increases and so stigma is reduced when the welfare recipiency rate for individuals of the same race in the community rises[9]. For instance, in a community with relatively many Whites and few Blacks on welfare, Whites tend to support welfare more than Blacks, and so Whites are stigmatized (as welfare recipients) by everybody, but more by Blacks than other Whites. This idea is captured by a stigma function $S(m_g, m_o)$ that is decreasing in the expected welfare participation rates in both reference and outer group, respectively. We can summarize the model with the following utility function over participation choice:

$$\begin{aligned} U_i(0) &= u(w) \\ U_i(1) &= u(T) - C(m_g) - S(m_g, m_o). \end{aligned} \tag{1}$$

An eligible individual uses welfare if and only if $U_i(1) \geq U_i(0)$. This defines a reservation wage, $\widehat{w}_g$, for each reference group, as the solution to the indifference condition $U_i(0) = U_i(1)$, which implies:

$$\widehat{w}_g = u^{-1}\left(u\left(T - C(m_g)\right) - S(m_g, m_o)\right). \tag{2}$$

An individual works if he can earn at least $\widehat{w}_g$ on the labor market, and chooses welfare otherwise. Therefore, the self-consistent solution for participation rates are the fixed points that satisfy $m_g = F(\widehat{w}_g(m_g))$, and

[9]This effect, which is revealed by survey data, is also discussed at lenght by Alesina and Glaeser (2004). We interpret the term more broadly to include ethnicity as well as race.

$m_o = F(\widehat{w}_o(m_o))$, where $F(w)$ is the distribution of wages in the economy. An equilibrium in this model is a set of reservation wages for each group, equation (2), and self-consistent participation rates. The equilibrium probability of welfare use, conditional on membership in group g, is

$$\Pr(\pi_{ig} = 1) = F\left(u^{-1}\left(u(T) - C(m_g) - S(m_g, m_o)\right)\right), \tag{3}$$

which is the object we want to estimate.

3 Econometric model

Consider a linear approximation for the solution to the theoretical model, equation (3). We define reference groups as race within PUMA. Adding individual controls, X_i, and group-level controls for race g in PUMA k, Y_g^k, and dropping the transfer variable T, which is redundant once individual controls are introduced, we end up with a linear probability model:

$$\Pr(\pi_{igk} = 1) = b_g + c_g X_i + d_g Y_g^k + J_g^{SC} m_g^k + J_o^S m_o^k, \tag{4}$$

whose parameters are estimated through the following regression model:

$$\pi_{igk} = b_g + c_g X_i + d_g Y_g^k + J_g^{SC} m_g^k + J_o^S m_o^k + \varepsilon_{igk}. \tag{5}$$

Here π_{igk} is a binary variable, equal to one if individual i of race g in PUMA k receives welfare transfers, and zero otherwise. The two social interactions coefficients J_g^{SC} and J_o^S capture, respectively, the joint effect of stigma (S) and information (C) from own race, and of stigma from other races, both within PUMAs. In Manski's (1993) terminology, c_g expresses individual effects, d_g contextual effects, and J_g^{SC} and J_o^S endogenous social effects. It is well known that a model like (5) suffers from several problems. An obvious one is how to define reference groups and the geographic level. We discuss our choice in the next section.

Four other problems, whose nature is more specifically econometric, deserve particular attention. The first is the *reflection problem* (Manski, 1993), which potentially affects any linear model with social interactions. Self consistency requires that the expected participation rate be equal to the mathematical expectation of the individual participation indicator, given the information available to the econometrician: $E\left[\pi_{igk}|X_i, Y_g^k, m_o^k\right] = m_g^k$. Taking conditional expectations of both sides, replacing and rearranging, the structural model (5) has the following reduced form:

$$\begin{aligned}\pi_{igk} &= \frac{b_g}{1-J_g^{SC}} + c_g X_i \frac{J_g^{SC} c_g}{1-J_g^{SC}} E\left(X_i | Y_g^k, m_o^k\right) \\ &\quad + \frac{d_g}{1-J_g^{SC}} Y_g^k + \frac{J_o^S}{1-J_g^{SC}} m_o^k + \varepsilon_{igk}\end{aligned} \tag{6}$$

If the mean of individual characteristics in the group, $E\left(X_i | Y_g^k, m_o^k\right)$, depends linearly on the group-level controls, Y_g^k, then the estimates from the reduced form cannot be used to recover the parameters of the structural form: this is just a matter of counting equations and unknowns.

The second problem is the *selection problem* (Heckman, 1978): although race is an exogenous trait, 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 equation (6) is not a valid regression equation, and the estimated social effects will be affected by selection bias. For example, McKinnish (2005) finds short-distance cross-border migration for the purpose of obtaining welfare benefits.

The third problem is the *group unobservables problem*. There may be unobservables at the PUMA level, such as the efficiency of the local welfare office, or the presence of alternatives to public welfare, that end up in the error term and that are also correlated with contextual controls. Both this and the selection problem are of course related to endogeneity.

The fourth problem can be labeled the *conflation problem*[10] (Manski, 2000). As discussed in the introduction, the decision to participate in welfare may be influenced by the members of some reference groups in a variety of ways, a fact we take into account when defining J_g^{SC}: this coefficient is the composite of stigma and information effects. Clearly, model (5) alone is not sufficient to identify them separately.

We deal with these problems as follows. The reflection problem is solved using one of the possibilities suggested by Brock and Durlauf (2001), namely imposing an exclusion restriction in the form of an individual effect whose average is not a contextual effect. We discuss below our preferred restriction,

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

which is then tested against alternative plausible ones. Next, we test the presence of selection bias instrumenting for the group-level variables, which are indirectly chosen through residential choices. We instrument each PUMA with its neighboring PUMA, according to Census maps. In order to solve the group unobservable problem, we re-estimate our main model using a random effects specification. This way we try to get rid of variables that are constant at the PUMA level, although the random effects hypothesis may be inappropriate in this context. If the results from this instrumenting approach are consistent with our original ones, it suggests that our method is not affected by the cross-border migration found in McKinnish (2005) and others. Finally, as mentioned above, the solution strategy for the conflation problem rests on the key assumption that one's own race group, g, at the PUMA level is a source of stigma and information, while the union of other race groups, o, at the PUMA level is a source on stigma only.

Specifically, our strategy to solve the conflation problem is as follows. Consider model (4) again, along with an auxiliary model, (8):

$$\Pr\left(\pi_{igk}=1\right)=b_g+c_gX_i+d_gY_g^k+J_g^{SC}m_g^k+J_o^Sm_o^k \tag{7}$$

$$\Pr\left(\pi_{igk}=1\right)=b_g+c_gX_i+d_gY_g^k+J_g^{C}m_g^k+J_{go}^S\left(\alpha_g m_g^k+\left(1-\alpha_g\right)m_o^k\right) \tag{8}$$

The linear function $J_{go}^S\left(\alpha_g m_g^k+\left(1-\alpha_g\right)m_o^k\right)$ in the auxiliary model is a "total stigma" function, which depends linearly on a convex combination of welfare participation rates of one's race and other races within PUMAs, with weight α_g to be discussed in a moment. This function captures social effects that, by construction, work within and across races. This leaves out information sharing, the only social effect that works within but not across races, which is captured by the function $J_g^Cm_g^k$ in the auxiliary model (8). The linearity of the latter may appear inappropriate, since the effect of information on the probability of welfare participation is nonlinear: for instance, if the percentage of individuals on welfare doubles, the information that one receives of course does not double. A small group of individuals on welfare may be enough for information to spread. Yet, the *probability* of being in contact with people who possess useful information may be a linear function of the share of individuals who possess it. The weight α_g is known, and is the demographic density of race g at the national level[11]. This imposes the following assumption. Stigma is a local effect, i.e. works at the PUMA level. However, the perceived stigma from a given group of people of any race is proportional to the demographic density of their races at the national, not local level. In other words, the racial composition of the country shapes social relations at the local level. This assumption is needed for identification, and we believe it has some plausibility: in our sample, the empirical density of race weights across PUMAs are concentrated around the national weights (computed from 2000 Census data) of 0.120 for Black (nonhispanic), 0.125 for Hispanic (of all races), and 0.691 for White (nonhispanic). The sample means (which consider women of working age only) are 0.114, 0.124, and 0.698.

Notice that, conditional on race, the auxiliary regression does not use new information, since α_g is a constant. This is why the coefficients on individual and contextual effects are the same in the two models. Therefore, the corresponding regression models have the same errors:

$$\pi_{igk} = b_g + c_g X_i + d_g Y_g^k + J_g^{SC} m_g^k + J_o^S m_o^k + \varepsilon_{igk} \tag{9}$$

$$\pi_{igk} = b_g + c_g X_i + d_g Y_g^k + J_g^C m_g^k + J_{go}^S \left(\alpha_g m_g^k + (1 - \alpha_g) m_o^k\right) + \varepsilon_{igk} \tag{10}$$

These two models are both "true models", and so one can compare the coefficients of different social effects across models. To summarize them:

- J_g^{SC} captures stigma and information effects from own race g.
- J_g^C captures the information effect from own race g.
- J_o^S captures stigma from other race groups o.
- J_{go}^S captures joint stigma from groups g and o.

Our estimator for the stigma effect from group g only, $\widehat{J}_g^S$, is the following:

$$\widehat{J}_g^S \equiv \widehat{J}_{go}^S - \widehat{J}_o^S, \tag{11}$$

[11] Notice that in this specification, the term $\alpha_g m_g^k$ is equivalent to the product of density of language and welfare use in Bertrand et al. (2000), which is the key to identification in their setting.

where the estimators on the right hand side are the OLS estimators[12]. This makes intuitive sense: since - under our assumptions - we can compare coefficients across models, to obtain the effect of stigma from group g only, we subtract from total stigma the portion that does not come from group g. By the same token, one could also write

$$\widehat{J}_g^S \equiv \widehat{J}_g^{SC} - \widehat{J}_g^C. \tag{12}$$

Of course these two estimators are equivalent under our assumptions. Computing marginal effects from the primary and auxiliary regression equations we get:

$$\begin{aligned}
\frac{\partial \Pr(\pi_{igk} = 1)}{\partial m_o^k} &= J_o^S = (1 - \alpha_g) J_{go}^S \\
\frac{\partial \Pr(\pi_{igk} = 1)}{\partial m_g^k} &= J_g^{SC} = J_g^C + \alpha_g J_{go}^S
\end{aligned}$$

Replace the first of these equations into (11):

$$J_g^S = J_{go}^S - (1 - \alpha_g) J_{go}^S = \alpha_g J_{go}^S,$$

and the second into (12):

$$J_g^S = J_g^C + \alpha_g J_{go}^S - J_g^C = \alpha_g J_{go}^S.$$

This provides a way to estimate J_g^S univocally, along with a useful specification test: if our model is correctly specified, the means of estimators (11) and (12) should provide the same estimate. As we report below, in our sample, these are close but not identical, which means what we are measuring is not simply the effect of stigma and information, which is not surprising. However, the two estimates are close enough to make us confident our model is meaningful. Although our estimators (11) and (12) are statistically well-behaved, their structural interpretation should be regarded as resting on an approximation. For instance, in estimating J_{go}^S through (11) it is assumed that stigma and identity from groups g and o are, so to speak, perfect substitutes, a restriction that is not imposed when estimating J_o^S. Therefore, (11)

[12] Although OLS is not efficient in the context of a linear probability model.

compares two estimators that incorporate two possibly conflicting views on the sensitivity of individuals to stigma from different groups. This possible logical inconsistency requires regarding $\widehat{J}_g^S$ as approximating the stigma effect from group g, without corresponding measures of precision; i.e. we have little understanding of the quality of this particular approximation.

Our simple theoretical model predicts that both J_g^C, the information effect and J_g^S and J_o^S, the stigma effects, are positive. Overall, this strategy isolates information, that is not a preference-based social effect, from other effects that operate through preferences, a distinction that may be important for policy evaluation. As discussed above, in order to identify the parameters of the structural models (9) and (10), we opt for an exclusion restriction that breaks possible collinearity between contextual and mean individual effects. Denoting with x the excluded variable and with superscript r its coefficient, we estimate the following reduced forms, which are derived exactly like equation (6):

$$\begin{aligned}\pi_{igk} &= \frac{b_g}{1-J_g^{SC}} + c_g X_i + c_g^r x_i + \frac{J_g^{SC} c_g}{1-J_g^{SCI}} E\left(X_i | Y_g^k, m_o^k\right) \\ &+ \frac{J_g^{SC} c_g^r}{1-J_g^{SC}} E\left(x_i | Y_g^k, m_o^k\right) + \frac{d_g}{1-J_g^{SCI}} Y_g^k + \frac{J_o^S}{1-J_g^{SC}} m_o^k + \varepsilon_{igk}\end{aligned} \tag{13}$$

$$\begin{aligned}\pi_{igk} &= \frac{b_g}{1-J_g^C} + c_g X_i + c_g^r x_i + \frac{J_g^C c_g}{1-J_g^C} E\left(X_i | Y_g^k, m_o^k\right) \\ &+ \frac{J_g^C c_g^r}{1-J_g^C} E\left(x_i | Y_g^k, m_o^k\right) + \frac{d_g}{1-J_g^C} Y_g^k + \frac{J_{go}^S}{1-J_g^C}\left(\alpha_g m_g^k + (1-\alpha_g) m_o^k\right) + \varepsilon_{igk},\end{aligned} \tag{14}$$

where $E\left(X_i | Y_g^k, m_o^k\right) \subseteq Y_g^k$ but, by restriction, $E\left(x_i | Y_g^k, m_o^k\right) \notin Y_g^k$. This allows one to recover all of the structural coefficients and standard errors from the reduced form ones, using the delta method.

4 Data description

We use data from the 2000 Census 5% PUMS (Public Use Microdata Sample). We will focus on two races and one ethnicity, at the PUMA level: Black

(B), Hispanic of any race (H), and White (W). As in any study of social interactions this is mainly a matter of judgement, as there is no reliable statistical way yet known to precisely identify reference groups, and of course our conclusions will be contingent on such judgement. We believe our choice makes sense for a study of social effects in welfare, in particular because the welfare debate in the United States has for some time been defined, for better or worse, on racial and ethnic lines. By defining our groups along these lines we are able to comment on the role that race and ethnicity plays in welfare decision-making in a world of social influences within and across races. The PUMA level of aggregation is made for convenience as it is the lowest level of aggregation available in PUMS. Though this area is relatively large to be considered a reference group in the traditional sense, we feel that it is a reasonable level of aggregation in which to consider race-based social effects. A PUMA composes 100,000 individuals, a size large enough to encompass regions within cities (e.g. a portion of Harlem), and small enough to define a couple of school districts. The dataset is constructed as follows, from raw data. After excluding institutional population, we restrict the sample to women between 15 and 55 years old, in order to capture only the working age population and to avoid an overlap with Social Security payments to those in older demographic brackets, as well as because welfare policy is targeted principally at families with children, a demographic that almost universally includes women[13]. Own-group effects are based on the actions of individuals of the same race within a PUMA. Outgroups are the remainder of the population in the given PUMA. Contextual variables are estimated using sample averages of individual variables, by race at the PUMA level. In order to assess how good these estimates are, we computed group size for each individual. It turns out that 63,913 individuals for which we calculate contextual variables by sample mean have less than 100 neighbors in the sample. Of course the law of large numbers cannot be invoked for many of these. However, they comprise only 2% of the sample. We also included in the dataset the number of social workers in the State of residence (source: Bureau of Labor Statistics). This is an important control variables when trying to identify information effects, because social workers spread information about welfare benefits availability and eligibility. Our final sample contains 376,346 Blacks, 422,314 Hispanic, 1,834,172 White nonhispanic, as well as 219,484 individuals of other races, which are included in the computation of

[13]Each of these follow Bertrand et al (2000).

welfare participation rates. Table 1 describes the variables we use, and table 2 contains descriptive statistics.

Table 1: Variables Used

Variable	**Description**
age	age
age2	age squared divided by 100
childpresent	whether kids are present in household
collegemore	whether has college degree or more
divorced	whether divorced
ftotinc	pre-tax family income (in 2000 US$)
hsdropout	whether high school dropout
hsgrad	whether high school graduate
inctot	pre-tax personal income (in 2000 US$)
incwelfr	income welfare (in 2000 US$)
marriedsabsent	whether married and spouse absent
nchild	number of kids in household
nevermarried	whether never married
poorenglish	whether speaks english poorly
poverty	family income as % of poverty threshold
separated	whether separated
singlemother	whether single mother
social workers	social workers per 1,000 people in State
somecollege	whether attended college
unemployed	whether unemployed
welfarepart	welfare participation indicator
widowed	whether widowed

Table 2a: descriptive statistics (all groups, pooled)

	Black		Hispanic		White	
	(n=376,346)		(n=422,314)		(n=1,834,172)	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
welfare	0.073	0.260	0.049	0.216	0.015	0.123
incwelfr	213.53	1,187.24	179.47	1,110.10	42.81	522.26
inctot	19,076.51	24,072.91	12,783.66	20,598.88	23,504.94	30,630.34
ftotinc	43,760.97	44,607.65	47,196.36	48,401.91	72,700.59	71,374.57
poverty	253.697	164.908	232.786	154.471	360.921	151.888
unemployed	0.071	0.257	0.061	0.239	0.027	0.162
individual						
age	34.436	11.362	32.417	10.929	36.311	11.318
age2	13.149	7.898	11.703	7.464	14.466	8.054
hsdropout	0.253	0.435	0.465	0.499	0.142	0.349
hsgrad	0.272	0.445	0.222	0.416	0.242	0.428
somecollege	0.327	0.469	0.221	0.415	0.326	0.469
collegemore	0.147	0.354	0.092	0.289	0.290	0.454
singlemother	0.299	0.458	0.148	0.356	0.097	0.296
marriedsabsent	0.028	0.166	0.037	0.188	0.010	0.099
widowed	0.024	0.153	0.015	0.123	0.013	0.114
divorced	0.127	0.333	0.081	0.272	0.118	0.323
separated	0.061	0.240	0.048	0.213	0.020	0.142
nevermarried	0.482	0.500	0.344	0.475	0.278	0.448
childpresent	0.521	0.500	0.556	0.497	0.484	0.500
nchild	0.998	1.235	1.212	1.389	0.897	1.125
poorenglish	0.009	0.096	0.264	0.441	0.008	0.088
contextual						
age	34.436	1.161	32.417	1.390	36.311	1.202
age2	13.149	0.825	11.703	0.966	14.466	0.856
hsdropout	0.253	0.077	0.465	0.138	0.142	0.045
hsgrad	0.272	0.059	0.222	0.046	0.242	0.083
somecollege	0.327	0.064	0.221	0.073	0.326	0.060
collegemore	0.147	0.081	0.092	0.071	0.290	0.139
singlemother	0.299	0.064	0.148	0.057	0.097	0.025
marriedsabsent	0.028	0.013	0.037	0.016	0.010	0.004
widowed	0.024	0.010	0.015	0.008	0.013	0.005
divorced	0.127	0.031	0.081	0.031	0.118	0.029
separated	0.061	0.019	0.048	0.021	0.020	0.009
nevermarried	0.482	0.077	0.344	0.058	0.278	0.072
childpresent	0.521	0.050	0.556	0.054	0.484	0.076
nchild	0.998	0.133	1.212	0.196	0.897	0.172
poorenglish	0.009	0.016	0.264	0.113	0.008	0.012
socworkers	1.842	0.652	1.708	0.578	1.983	0.765

Table 2b: descriptive statistics (Black only)

	Black					
	All (n=376,346)		On welfare (n=27,485)		Not on welfare (n=348,861)	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
welfare	0.073	0.260	1	0	0	0
incwelfr	213.53	1,187.24	2,923.77	3,372.96	0	0
inctot	19,076.51	24,072.91	10,575.06	17,997.93	19,746.29	24,361.84
ftotinc	43,760.97	44,607.65	20,822.37	31,229.98	45,568.23	45,000.61
poverty	253.697	164.908	114.320	115.169	264.678	163.221
unemployed	0.071	0.257	0.178	0.382	0.063	0.243
individual						
age	34.436	11.362	33.348	9.743	34.521	11.476
age2	13.149	7.898	12.070	6.829	13.234	7.970
hsdropout	0.253	0.435	0.413	0.492	0.240	0.427
hsgrad	0.272	0.445	0.336	0.472	0.267	0.443
somecollege	0.327	0.469	0.226	0.419	0.335	0.472
collegemore	0.147	0.354	0.025	0.155	0.157	0.364
singlemother	0.299	0.458	0.636	0.481	0.272	0.445
marriedsabsent	0.028	0.166	0.037	0.188	0.028	0.164
widowed	0.024	0.153	0.025	0.157	0.024	0.152
divorced	0.127	0.333	0.120	0.324	0.128	0.334
separated	0.061	0.240	0.102	0.303	0.058	0.234
nevermarried	0.482	0.500	0.628	0.483	0.471	0.499
childpresent	0.521	0.500	0.738	0.440	0.504	0.500
nchild	0.998	1.235	1.725	1.551	0.941	1.188
poorenglish	0.009	0.096	0.007	0.086	0.009	0.097
contextual						
age	34.436	1.161	34.298	1.049	34.446	1.169
age2	13.149	0.825	13.068	0.746	13.156	0.831
hsdropout	0.253	0.077	0.278	0.070	0.251	0.077
hsgrad	0.272	0.059	0.282	0.053	0.271	0.060
somecollege	0.327	0.064	0.319	0.063	0.328	0.064
collegemore	0.147	0.081	0.121	0.062	0.149	0.082
singlemother	0.299	0.064	0.327	0.057	0.297	0.064
marriedsabsent	0.028	0.013	0.030	0.012	0.028	0.013
widowed	0.024	0.010	0.026	0.010	0.024	0.010
divorced	0.127	0.031	0.124	0.031	0.127	0.031
separated	0.061	0.019	0.065	0.019	0.061	0.019
nevermarried	0.482	0.077	0.515	0.072	0.480	0.076
childpresent	0.521	0.050	0.522	0.047	0.521	0.051
nchild	0.998	0.133	1.019	0.133	0.996	0.133
poorenglish	0.009	0.016	0.009	0.015	0.009	0.016
socworkers	1.842	0.652	1.889	0.720	1.839	0.646

Table 2c: descriptive statistics (Hispanic only)

	Hispanic					
	All (n=422,314)		On welfare (n=20,625)		Not on welfare (n=401,689)	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
welfare	0.049	0.216	0	0	0	0
incwelfr	179.47	1,110.10	3,519.86	0	0	0
inctot	12,783.66	20,598.88	16,323.66	12,964.04	19,746.29	24,361.84
ftotinc	47,196.36	48,401.91	32,274.57	48,399.08	45,568.23	45,000.61
poverty	232.786	154.471	106.345	238.794	264.678	163.221
unemployed	0.061	0.239	0.336	0.057	0.063	0.243
individual						
age	32.417	10.929	9.475	32.358	34.521	11.476
age2	11.703	7.464	6.655	11.680	13.234	7.970
hsdropout	0.465	0.499	0.484	0.457	0.240	0.427
hsgrad	0.222	0.416	0.413	0.223	0.267	0.443
somecollege	0.221	0.415	0.342	0.225	0.335	0.472
collegemore	0.092	0.289	0.139	0.096	0.157	0.364
singlemother	0.148	0.356	0.500	0.130	0.272	0.445
marriedsabsent	0.037	0.188	0.217	0.036	0.028	0.164
widowed	0.015	0.123	0.157	0.015	0.024	0.152
divorced	0.081	0.272	0.350	0.078	0.128	0.334
separated	0.048	0.213	0.359	0.042	0.058	0.234
nevermarried	0.344	0.475	0.488	0.341	0.471	0.499
childpresent	0.556	0.497	0.422	0.545	0.504	0.500
nchild	1.212	1.389	1.593	1.174	0.941	1.188
poorenglish	0.264	0.441	0.462	0.262	0.009	0.097
contextual						
age	32.417	1.390	1.222	32.419	34.446	1.169
age2	11.703	0.966	0.854	11.703	13.156	0.831
hsdropout	0.465	0.138	0.120	0.463	0.251	0.077
hsgrad	0.222	0.046	0.045	0.223	0.271	0.060
somecollege	0.221	0.073	0.063	0.221	0.328	0.064
collegemore	0.092	0.071	0.054	0.093	0.149	0.082
singlemother	0.148	0.057	0.078	0.147	0.297	0.064
marriedsabsent	0.037	0.016	0.017	0.037	0.028	0.013
widowed	0.015	0.008	0.008	0.015	0.024	0.010
divorced	0.081	0.031	0.030	0.081	0.127	0.031
separated	0.048	0.021	0.026	0.047	0.061	0.019
nevermarried	0.344	0.058	0.062	0.342	0.480	0.076
childpresent	0.556	0.054	0.048	0.556	0.521	0.051
nchild	1.212	0.196	0.181	1.210	0.996	0.133
poorenglish	0.264	0.113	0.108	0.264	0.009	0.016
socworkers	1.708	0.578	0.703	1.698	1.839	0.646

Table 2d: descriptive statistics (White only)

	White					
	All (n=1,834,172)		On welfare (n=27,974)		Not on welfare (n=1,806,198)	
Variable	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
welfare	0.015	0.123	1	0	0	0
incwelfr	42.81	522.26	2,806.73	3,182.23	0	0
inctot	23,504.94	30,630.34	11,617.66	16,248.51	23,689.05	30,764.22
ftotinc	72,700.59	71,374.57	27,967.31	37,548.37	73,393.42	71,553.64
poverty	360.921	151.888	159.077	140.265	364.047	149.939
unemployed	0.027	0.162	0.095	0.293	0.026	0.158
individual						
age	36.311	11.318	34.274	9.810	36.343	11.337
age2	14.466	8.054	12.709	6.986	14.493	8.067
hsdropout	0.142	0.349	0.314	0.464	0.139	0.346
hsgrad	0.242	0.428	0.353	0.478	0.240	0.427
somecollege	0.326	0.469	0.267	0.443	0.327	0.469
collegemore	0.290	0.454	0.066	0.248	0.293	0.455
singlemother	0.097	0.296	0.458	0.498	0.091	0.288
marriedsabsent	0.010	0.099	0.027	0.161	0.010	0.098
widowed	0.013	0.114	0.022	0.148	0.013	0.114
divorced	0.118	0.323	0.279	0.448	0.116	0.320
separated	0.020	0.142	0.099	0.299	0.019	0.137
nevermarried	0.278	0.448	0.342	0.474	0.277	0.447
childpresent	0.484	0.500	0.666	0.472	0.481	0.500
nchild	0.897	1.125	1.316	1.293	0.890	1.121
poorenglish	0.008	0.088	0.023	0.149	0.008	0.087
contextual						
age	36.311	1.202	36.089	1.126	36.315	1.203
age2	14.466	0.856	14.322	0.801	14.468	0.857
hsdropout	0.142	0.045	0.160	0.049	0.142	0.045
hsgrad	0.242	0.083	0.260	0.075	0.241	0.083
somecollege	0.326	0.060	0.337	0.059	0.326	0.060
collegemore	0.290	0.139	0.244	0.115	0.290	0.140
singlemother	0.097	0.025	0.110	0.028	0.097	0.025
marriedsabsent	0.010	0.004	0.011	0.005	0.010	0.004
widowed	0.013	0.005	0.015	0.005	0.013	0.005
divorced	0.118	0.029	0.128	0.030	0.118	0.029
separated	0.020	0.009	0.024	0.011	0.020	0.009
nevermarried	0.278	0.072	0.286	0.072	0.278	0.072
childpresent	0.484	0.076	0.480	0.070	0.484	0.076
nchild	0.897	0.172	0.889	0.161	0.897	0.173
poorenglish	0.008	0.012	0.010	0.017	0.008	0.012
socworkers	1.983	0.765	2.006	0.783	1.983	0.765

Our indicator of welfare usage is a dummy variable that is set equal to one if an individual receives any public assistance income other than social security. The Census bureau's measure of welfare usage includes both Temporary Assistance for Needy Families (TANF) (the replacement Aid to Families with Dependent Children (AFDC)) as well as housing subsidies, food stamps, and the Woman, Infants and Children (WIC) program[14]. As shown, we use a simple set of individual controls ranging from school achievement to marital status. High school dropout is a indicator for any individual that did not complete high school and is above age 18. High school graduate is any that completed school or obtained a equivalency diploma. Some college refers to individuals that started but did not complete college. The omitted group (to avoid perfect collinearity) is college graduates. The variables for number of children, presence of children in household, and single mother are self-explanatory. The marital status variables are similarly straightforward and taken directly from Census definitions. We use married, spouse present as the omitted category here.

As for our identifying restriction, we assume that the number of children in a household affects the individual probability of being on welfare, but the average number of children per household in a PUMA does not. Of all the available variables this seems to us the most suitable for such a restriction: of course the number of children in a household affects the probability of being on welfare (think of single mothers), but we see no reason why the average number of children per household, conditional on race, in a PUMA should have a bearing on the individual likelihood of receiving welfare transfers, after controlling for the percentage of households with kids. We will consider alternative restrictions momentarily.

5 Results

We estimated models (13)-(14) by Ordinary Least Squares (OLS), Random Effects (RE) and Instrumental Variables (IV). Our principal empirical result is that social interactions have a large and significant role in the decision to participate in welfare. Moreover, social effects–like individual and contextual effects–differ by racial group. Table 3 contains our OLS estimates of individual and contextual effects. Tables 4 and 5 contain our key results, namely

[14]Note that food stamps and WIC subsidies are in-kind and may not be reported by individuals as welfare assistance.

the estimated social interactions (peer effects).

Table 3: Individual and Contextual Effects (OLS)

	Black		Hispanic		White	
	individual	**contextual**	**individual**	**contextual**	**individual**	**contextual**
age	0.011	-0.004	0.008	-0.012	0.004	-0.003
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
age2	-0.015	0.00722	-0.011	0.017	-0.006	0.004
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
hsdropout	0.096	-0.070	0.044	-0.056	0.035	-0.017
	(0.001)***	(0.005)***	(0.001)***	(0.003)***	(0.000)***	(0.002)***
hsgrad	0.052	-0.059	0.025	-0.044	0.016	-0.02
	(0.001)***	(0.003)***	(0.001)***	(0.003)***	(0.000)***	(0.001)***
somecollege	0.018	0.015	0.008	-0.011	0.006	-0.001
	(0.001)***	(0.004)***	(0.001)***	(0.004)***	(0.000)***	(0.001)*
singlemother	0.102	-0.002	0.125	0.029	0.057	-0.021
	(0.002)***	(.009)	(0.002)***	(0.012)**	(0.000)***	(0.003)***
marriedsabsent	0.053	-0.037	0.042	-0.007	0.032	0.023
	(0.003)***	(0.011)***	(0.002)***	(.008)	(0.001)***	(0.006)***
widowed	-0.012	0.010	-0.028	-0.012	-0.008	0.005
	(0.003)***	(.014)	(0.003)***	(.014)	(0.001)***	(.005)
divorced	-0.016	0.003	-0.008	-0.036	0.001	-0.002
	(0.002)***	(.008)	(0.002)***	(0.008)***	(0.000)***	(.002)
separated	0.006	-0.044	0.031	-0.018	0.026	-0.012
	(0.002)***	(0.009)***	(0.002)***	(0.008)**	(0.001)***	(0.003)***
nevermarried	0.03	-0.001	0.024	-0.008	0.009	-0.004
	(0.002)***	(.006)	(0.001)***	(0.004)*	(0.000)***	(0.001)***
childpresent	-0.057	-0.035	-0.031	-0.010	-0.01	-0.003
	(0.002)***	(0.006)***	(0.001)***	(0.004)**	(0.000)***	(0.001)***
nchild	0.035		0.019		0.006	
	(0.001)***		(0.000)***		(0.000)***	
constant	-0.157		0.051		-0.026	
	(0.020)***		(0.015)***		(0.003)***	
Observations	376,346		422,314		1,834,172	
R-squared	0.1		0.09		0.04	

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Endogenous Social Effects (OLS and RE)

	Ordinary Least Squares			Random Effects		
	Black	**Hispanic**	**White**	**Black**	**Hispanic**	**White**
stigma and info own race	0.701	0.699	0.806	0.701	0.645	0.863
	(0.017)***	(0.023)***	(0.014)***	(0.017)***	(0.045)***	(0.019)***
info own race	**0.662**	**0.663**	**0.605**	**0.662**	**0.639**	**0.660**
	(0.022)***	(0.029)***	(0.046)***	(0.022)***	(0.038)***	(0.067)***
stigma other races	**0.163**	**0.087**	**0.024**	**0.163**	**0.130**	**0.017**
	(0.011)***	(0.008)***	(0.002)***	(0.011)***	(0.019)***	(0.003)***
stigma own and other races	0.237	0.126	0.219	0.237	0.155	0.199
	(0.017)***	(0.012)***	(0.032)***	(0.017)***	(0.018)***	(0.040)***
stigma own race	**0.028**	**0.016**	**0.151**	**0.028**	**0.019**	**0.138**
	(0.002)***	(0.002)***	(0.022)***	(0.002)***	(0.002)***	(0.028)***
test:						
equation 11	0.074	0.039	0.195	0.074	0.025	0.182
equation 12	0.039	0.036	0.201	0.039	0.006	0.203

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Consider the left panel (OLS) first. The total social effect from own race, J_g^{SC}, is strong for all three groups (Black, White and Hispanic). However, while information, J_g^C, explains most of these effects for Blacks and Hispanics, Whites are subject to a relatively strong stigma effect from other Whites, J_g^S, within PUMAs. As for cross-group social effects, minorities–and Blacks in particular–are subject to stigma from other groups, J_o^S, more than White. To relate this to the overly 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 a function of own-group stigma as well.

The right panel (RE) shows that these results are highly robust to a random effects specification. This random effects specification addresses possible PUMA-specific unobservables. That is, we estimated

$$
\begin{aligned}
\pi_{igk} &= \frac{b_g}{1-J_g^{SC}} + c_g X_i + c_g^r x_i + \frac{J_g^{SC} c_g + d_g}{1-J_g^{SC}} Y_g^k \\
&\quad + \frac{J_g^{SC} c_g^r}{1-J_g^{SCI}} E\left(x_i | Y_g^k, m_o^k\right) + \frac{J_o^S}{1-J_g^{SC}} m_o^k + \delta_k + \varepsilon_{igk} \\
\pi_{igk} &= \frac{b_g}{1-J_g^C} + c_g X_i + c_g^r x_i + \frac{J_g^C c_g + d_g}{1-J_g^C} Y_g^k \\
&\quad + \frac{J_g^C c_g^r}{1-J_g^C} E\left(x_i | Y_g^k, m_o^k\right) + \frac{J_{go}^S}{1-J_g^C} \left(\alpha_g m_g^k + (1-\alpha_g) m_o^k\right) + \delta_k + \varepsilon_{igk},
\end{aligned}
$$

where δ_k is unobserved heterogeneity, constant within PUMAs. We are aware that the random effects assumption–that is, δ_k is orthogonal to the set of regressors–may be inappropriate in a social interactions context, and so the RE results may be as biased as the OLS ones in case of unobserved group effects. However, this is the simplest thing one can do given the nature of the data.

In table 5, we report the results of IV estimation, which is a popular choice against possible selection-bias. The idea is that through residential decisions, individuals choose the contextual variables used as regressors. As a consequence, these are likely to be correlated with the error term. We constructed two sets of "naive" instruments, which we used alternatively. By naive, we mean that we instrumented each PUMA, first using its successor (right adjacent) PUMA, then using its predecessor (left adjacent) PUMA, both times within US states according to the Census Bureau mapping system. This procedure, which seems legitimate as the characteristics of adjacent PUMAs are likely to be correlated, is illustrated in figure 5. In this respect, we are reassured by the fact that the two sets of instruments produce similar results.

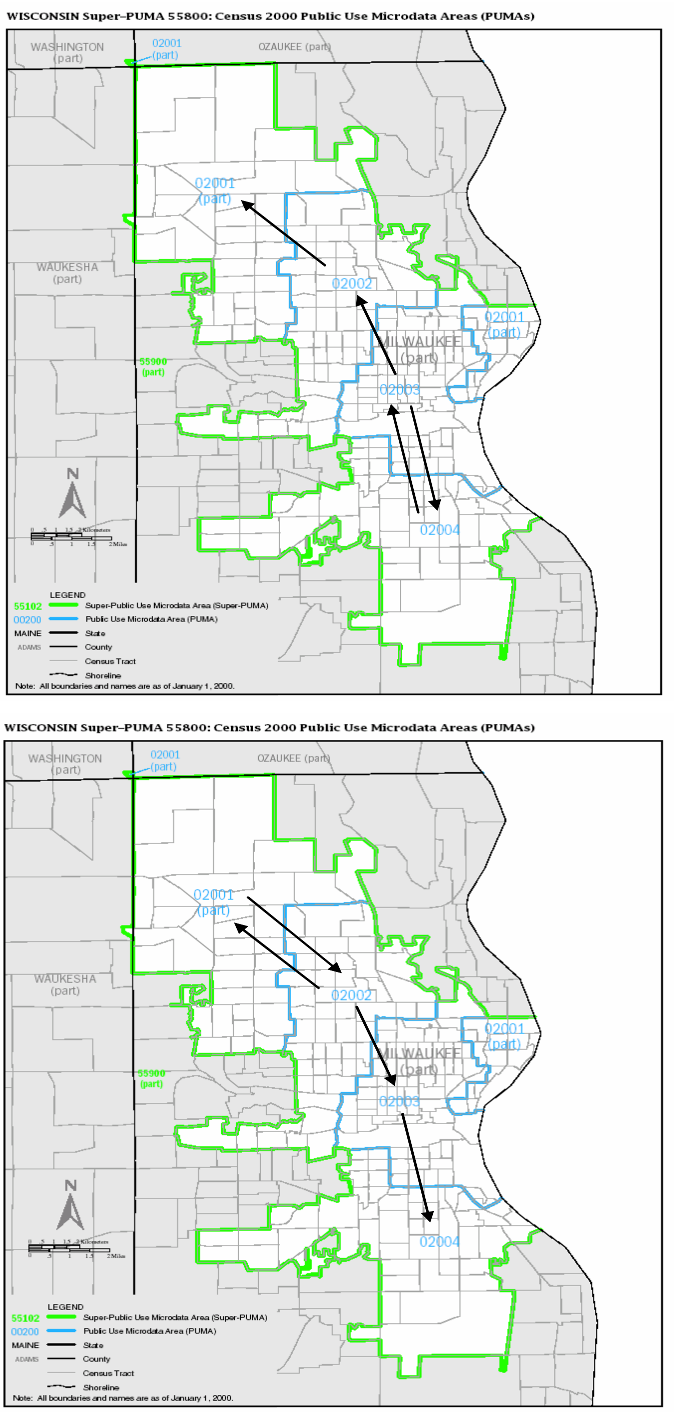

Fig. 5: Construction of right adjacent (upper panel) and left adjacent (lower panel) instruments for the Milwaukee metropolitan area.

Table 5: Endogenous Social Effects (IV)

	IV: right adjacent			IV: left adjacent		
	Black	**Hispanic**	**White**	**Black**	**Hispanic**	**White**
stigma and info own race	1.638	1.116	0.823	1.627	0.976	1.085
	(1.853)	(0.057)***	(0.241)***	(2.431)	(0.009)***	(0.109)***
info own race	**1.736**	**1.099**	**0.281**	**2.647**	**1.214**	**0.884**
	(2.514)	(0.043)***	(3.970)	(9.775)	(0.302)***	(0.081)***
stigma other races	**-0.345**	**0.013**	**0.043**	**-0.352**	**0.000**	**-0.016**
	(1.150)	(0.015)	(0.067)	(1.478)	(0.007)	(0.029)
stigma own and other races	-0.406	0.002	0.551	-1.227	-0.178	0.099
	(1.556)	(0.014)	(3.076)	(7.257)	(0.199)	(.064)
stigma own race	**-0.486**	**0.000**	**0.381**	**-0.147**	**-0.022**	**0.068**
	(.0186)	(0.002)	(2.125)	(0.869)	(0.025)	(0.044)
test:						
equation 11	-0.061	-0.011	0.508	-0.875	-0.178	0.115
equation 12	-0.098	0.017	0.542	-1.020	-0.238	0.201

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

When instrumenting this way for PUMA, we still find that information is the predominant within-group social effect, although all social effects in the Black subsample become insignificant. In general IV estimation to eliminate bias produced by group selection is quite difficult [15].

Finally, we performed robustness tests using alternative identifying restrictions. Our restriction so far has been that after controlling for the percentage of households that have kids within one's own race at the PUMA level, the average number of kids has no contextual effect. Table 6 contains the results of OLS estimation using four variables whose average is alternatively assumed not to be a contextual effect. The upper part of the table uses age and age squared. Although both can be seen as risk factors in predicting welfare participation, one can argue that the average age of a certain group needs not exert any contextual effect on group members. The lower part of table 6 uses the percentage of group members that never married and the percentage of single mothers. The results are strikingly similar across all these alternative restrictions. The assumption that the percentage of single mothers do not exert any contextual effect is of course the least plausible. However, it is possible that all the effect of this variable is already captured

[15] See Blume and Durlauf (2006) for a discussion.

by the participation rate, which may explain why this implausible restriction yields results similar to more plausible ones.

Table 6: OLS results under alternative restrictions.

	restriction: childpresent			**restriction: nevermarried**		
	Black	Hispanic	White	Black	Hispanic	White
stigma and info own race	0.815	0.741	0.854	0.704	0.576	0.669
	(0.016)***	(0.044)***	(0.017)***	(0.059)***	(0.109)***	(0.055)***
info own race	**0.795**	**0.700**	**0.313**	**0.626**	**0.521**	**0.462**
	(0.020)***	(0.058)***	(0.354)	(0.093)***	(0.139)***	(0.143)***
stigma other races	**0.101**	**0.075**	**0.018**	**0.160**	**0.123**	**0.040**
	(0.009)***	(0.013)***	(0.002)***	(0.033)***	(0.032)***	(0.007)***
stigma own and other races	0.144	0.112	0.381	0.263	0.180	0.298
	(0.014)***	(0.022)***	(0.197)*	(0.066)***	(0.053)***	(0.080)***
stigma own race	**0.017**	**0.014**	**0.263**	**0.031**	**0.023**	**0.206**
	(0.002)***	(0.003)***	(0.136)*	(0.008)***	(0.007)***	(0.055)***
test:						
equation 11	0.043	0.037	0.363	0.103	0.057	0.258
equation 12	0.020	0.041	0.541	0.078	0.055	0.207

	restriction: singlemother		
	Black	Hispanic	White
stigma and info own race	0.694	0.718	0.691
	(0.023)***	(0.014)***	(0.021)***
info own race	**0.653**	**0.692**	**-0.994**
	(0.030)***	(0.016)***	(0.868)
stigma other races	**0.166**	**0.082**	**0.038**
	(0.014)***	(0.05)***	(0.003)***
stigma own and other races	0.244	0.116	1.107
	(0.022)***	(0.008)***	(0.487)**
stigma own race	**0.029**	**0.014**	**0.764**
	(0.003)***	(0.001)***	(0.337)**
test:			
equation 11	0.078	0.034	1.069
equation 12	0.041	0.026	1.685

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

6 Discussion

How plausible is the result that information sharing is the predominant social effect? After all information is very easily spread. We constructed an index of welfare eligibility to check whether eligible nonparticipants in our sample have some special feature that justifies the information hypothesis. The index is constructed considering single mothers with kids less than 18 years old and with family income below the poverty threshold (adjusted to take into account family composition). This should identify at least all welfare eligible individuals. Unfortunately we have no data on assets, and so our index is likely to overestimate the number of eligible individuals. The means of a selected number of individual-level variables are reported in Table 7.

Table 7: Comparing welfare participants and eligible nonparticipants.

	Black		**Hispanic**		**White**	
	WP (n=27,485)	ENP (n=24,073)	WP (n=20,625)	ENP (n=14,608)	WP (n=27,974)	ENP (n=23,366)
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
hsdropout	0.413	0.334	0.627	0.563	0.314	0.241
hsgrad	0.336	0.373	0.218	0.240	0.353	0.362
somecollege	0.226	0.263	0.135	0.166	0.267	0.320
college or more	0.025	0.030	0.020	0.031	0.066	0.077
poor english	0.007	0.007	0.310	0.300	0.023	0.008
no phone	0.107	0.098	0.090	0.078	0.068	0.057

WP = Welfare Participant

ENP = Eligible NonParticipant

The table shows that it turns such "eligible nonparticipants" have lower dropout rates, higher rates of high school graduation and college attendance, as well as better English proficiency and higher rates of phone availability. The information hypothesis would predict the opposite for all these. It is possible that information on assets is critical in this context. Since we are working with a cross section we may be missing important dynamic factors. For instance, imagine a relatively better educated woman who comes on hard time–she'll be less likely to participate if she has assets available from a prior job. Nonetheless, this evidence calls for more research: either in the direction of constructing a better eligibility index, or in the direction of reconsidering our "separating assumption". While it is innocuous to focus on two effects, one of which works within and across groups and the other within only, we may be wrong in assuming that the latter corresponds to information, although it seems to us more plausible than the reverse.

7 Conclusion

In this paper we have argued that when trying to estimate the effect of social interactions on economic behavior, one needs to explicitly address the fact that different social effects, with different policy implications, are possibly at work. We have illustrated this point in the context of welfare participation in the US. Separate identification of stigma and information effects in this paper rests crucially on two restrictions. First, we have assumed that a certain group is a source of information and stigma while a different group is a source of stigma only. Second, we have assumed that one individual effect is not a contextual effect at the group level. We are well aware, as Manski (2000) puts it, that our empirical findings "are only as credible as the particular exclusion restrictions and modeling assumptions imposed" (p. 124). Nonetheless, 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 races. This in turn, is important to understand the working of welfare and to evaluate alternative policies.

Our empirical findings suggest that the popular characterization of welfare cultures in which individuals choose welfare over work may not be an accurate one. This characterization would be partially upheld with a finding of large own-group stigma effects. We find that the participation decisions of minority groups in our sample (women of working age) are based on demographic and socioeconomic characteristics as well as information availability.

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