Reconsidering Social Capital: A Latent Class Approach

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Abstract

Social capital has proven to be a useful concept, but has been ill-defined and not well-measured in the economics literature. We propose a different empirical method for measuring social capital, latent class analysis, based on the idea that social capital is an unobservable multidimensional construct. We explain and demonstrate the construction of latent classes that measure an individual's social capital using data from the General Social Survey. We then show our proposed method allows meaningfully different conclusions about the accumulation of social capital than those obtained by previous research. Specifically, we present evidence consistent with the hypothesis that higher income influences social capital accumulation because of a higher opportunity cost of time. In addition, we find evidence for complementarities in social capital accumulation within an individual's peer group.

1 Introduction

In the last few years, the concept of social capital has proven to be useful to economists in a wide range of fields because it helps to explain how individual and country-level social values and norms influence economic behavior and impact the successful design and implementation of economic policies.[1] However, as many researchers have pointed out, the concept has been ill-defined and imperfectly measured; often the measurement of social capital has implied the definition. This paper contributes to the literature by proposing and applying a new method to measure social capital, latent class models, based on the idea that social capital is an unobservable multidimensional construct.

Our work is motivated by the varying definitions and uses of the term social capital in the economics literature. Even a casual reading of the literature will show that this potentially useful concept takes on many forms. Sobel (2002) describes social capital as circumstances in which individuals can benefit from group membership. The World Bank, however, focuses on social capital as an aggregate, stating on its web site that it is the "norms and networks that enable collective action." Still others focus not on social connections and group membership, but on trust among individuals. The seminal paper by Knack and Keefer (1997) showed an important role for trust at the country level in explaining economic growth, while, at the individual level, Karlan (2005) uses laboratory experiments to measure trust, arguing that these experiments measure social capital and are helpful in explaining individual behavior. However, Guinnane (2005) argues that trust is not a useful concept at all because it cannot be separated from the quality of institutions. Finally, Durlauf and Fafchamps (2004) discuss the many different definitions of social capital in empirical research and assert that research on social capital is plagued by "conceptual vagueness." Thus, the concept of social capital has been broadly defined and even more broadly applied, running the risk of becoming a useless catch-all concept.

Rather than proposing another definition of social capital, we focus on two common basic components of the term to motivate our methodology. First, social capital is a multidimensional concept: it can embed multiple manifestations of civic engagement

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[1] See for example, Easterly and Levine (1997), Golden and Katz (1999), Narayan and Pritchett (1999), or Guiso, Sapienza aand Zingales (2002) for a broad range of examples. Interested readers should also see Durlauf and Fafchamps (2004) who provide a survey and critical analysis of this literature.

as well as trust and fairness. A useful measurement of social capital must account for as many of these dimensions as possible. Second, as researchers have pointed out, unlike physical or human capital, social capital is not necessarily beneficial to society at large (Durlauf and Fafchamps, 2004) – we can think of, as extreme cases, widespread civic engagement in Nazi Germany and involvement in terrorists and racist networks. More generally, individuals' values and socio-economic characteristics can attract them to different types of social networks that have, in turn, different effects on the economic system. Furthermore, an emphasis on the types of social capital is important from the point of view of public policy since, as Durlauf and Fafchamps (2004) argue, "it is social structures, not their consequences, which can be influenced by policymakers." This emphasis on the typology of social capital becomes important in empirical applications. Much of the discussion about Putnam's claim in *Bowling Alone* (2000) that civil engagement in the United States has declined centers on how civic engagement itself is measured. In particular, Durlauf and Fafchamps (2004) and Skocpol (2003) have argued that it is more appropriate to talk about changes in the nature of civic engagement than to talk about changes in the quantity of civic engagement. Thus, we must apply a methodology that generates a typology of social capital that accounts for the different incentives that networks provide and the various and even divergent effects that those networks might have on economic choices and outcomes.

We propose applying latent class models. This methodology is very promising because it approaches social capital as a multidimensional concept that can embed different aspects of the term used in the literature (group membership vs. trust) and, in doing so, allows for more nuanced conclusions about the amount and type of social capital possessed by individuals, how it is accumulated, and its impact on economic behavior. While our paper focuses primarily on identifying social capital in individuals, we discuss in the conclusion how our approach could be applied to the measurement of social capital at the country level.

In an example that compares our approach to recent findings, we show that measuring the types of social capital individuals hold does matter. Specifically, we replicate the models in Glaeser, Laibson, and Sacerdote (2002). While Glaeser, Laibson, and Sacerdote measure social capital as the number of voluntary organization memberships individuals hold, we use latent class analysis to classify individuals into distinct types of social capital using both memberships and indicators of trust and fairness. Using the same data, we find peer-group effects that Glaeser, Laibson and Sacerdote predict in their theoretical model but cannot identify empirically. Importantly, we find results consistent with the hypothesis that individuals with high opportunity cost of time choose networks with relatively low time commitment and perhaps high monetary cost. We also find that socio-economic determinants sort individuals into types of social capital that vary in the nature of the social network, but not necessarily in the number of memberships forming the network.

Although many researchers agree social capital is a multidimensional concept, few have applied multivariate methods. Sabatini (2005) uses principal components analysis to reduce a set of indicators of social capital (including memberships) to a single variable and Paxton (1999) applies confirmatory factor analysis to several indicators of trust. Our approach shares the same motivation and strengths of these analyses because we use multiple indicators of social capital. However, latent class models have some advantages over principal components analysis (PCA) and factor analysis (FA). First, the results of FA and PCA are generally not unique as researchers can "rotate" factor loadings to obtain a meaningful interpretation of the solution. Latent class analysis, on the other hand, is model-based and there exist formal criteria to decide on the dimensionality of the latent variable, that is, there are formal criteria to decide on the number of types of social capital that are present in the data. In addition, the interpretation of latent classes is based on the structure of their conditional probabilities. More importantly, PCA and FA assume that the observed indicators and the unobserved underlying factors are continuous and normally distributed. In some cases, however, it is more reasonable and in accordance with the theory to assume that social capital is a categorical variable and to characterize individuals according to the types of social-capital networks they belong to. Moreover, as we noted earlier, from the point of view of public policy it might be more important to measures types of social capital rather than the amount of social capital.[2]

[2] A typology of social capital from FA or PCA can be obtained, however, the process is more arbitrary than that used by latent class analysis. Specifically, the researcher would need to calculate factor scores of each

In what follows, we first introduce our empirical approach to measuring social capital using latent class analysis and then discuss the results of our latent class models. In Section 4 we use the results of the latent class models in an estimation that mirrors that of Glaeser, Laibson, and Sacerdote (2002) to demonstrate that our proposed approach to empirically treating social capital generates new insights about social capital formation. Section 5 summarizes the findings and discusses further applications of latent class models to the economics of social capital.

2 Using Latent Class Analysis to Measure Social Capital

In this section we describe and motivate the use of latent class analysis in order to measure social capital using 18 questions from the General Social Survey (GSS) that are common proxies for networks, norms, and trust. We use sixteen questions about membership in voluntary organizations and two questions regarding whether people can generally be trusted and whether other people are fair or try to take advantage of others. Our approach is to categorize individuals into types of social capital using a latent class (or finite-mixture) model that assigns people to classes that vary in the pattern of their probability structure.

Our approach can be defended on theoretical grounds. Although researchers commonly use the number of memberships in voluntary organizations as a proxy for social capital, the number of organizations an individual belongs to may not be as important as the nature of the organizations. Furthermore, in formulating policy implications, it is important to investigate whether different types of social capital influence economic decisions differently. For example, we should expect that the socio-demographic profile of individuals joining a union and a fraternal organization is different than the profile of individuals joining literary and hobby clubs. Likewise, the economic impact of social networks formed around labor unions and fraternal organizations is likely different than the influence of networks of literary and hobby clubs. Thus, researchers need a categorical variable that distinguishes among types of social networks. Such typology can be constructed by applying latent class modeling to

individual for each factor loading. Then, the researcher would need to determine a cut-off point for the factor scores and cross-tabulate below and above the cut-off point in order to obtain clusters of respondents.

the usual indicators of social capital. In what follows we show that our approach can also be defended on practical grounds as it produces new insights into social capital formation.

Although we believe our approach has many advantages, naturally, it also has limitations. In particular, data availability restricts us to considering the number of memberships rather than the strength of engagement in groups when classifying individuals into different social capital groups. However, this criticism can be rightly levied at many empirical studies of social capital. To some extent, our treatment of social capital, which also incorporates attitudes towards trust and fairness and uses membership in groups only as indicator variables of the latent class somewhat addresses this concern, though we admit it does so imperfectly.

The Method

Intuitively, one might think of latent class analysis as an alternative to using dummy variables that correspond to unique response patterns. For example, in the GSS data, we observe the answers to 18 different questions with binary outcomes and 2^{18} or 262,144 possible unique response patterns, of which 3,027 are represented in our data. If we were to consider each observed response pattern a unique type of social capital, then we would need to include 3,026 dummy variables in regression models explaining economic behavior. This exercise would provide regression models that are cumbersome to estimate and results that are very difficult to interpret. Instead, latent class analysis examines response patterns and groups individuals by these patterns. In our application, it reduces the possible response patterns down to seven distinct classes or types of social capital.

Latent class models are part of the family of finite mixture models firmly grounded in a probability framework that allows model testing and the calculation of goodness-of-fit measures. Although latent class analysis has been applied to several social issues (see, for example, Patterson et al. 2002; and Biemer and Wiesen, 2002), it is still a fairly novel methodology in the economics literature. (See Boxall and Adamowicz, 2002; Greene and Hensher, 2003; Clark, Etile, Postel-Vinay, Senik and Van der Straeten, 2005; and Morey, Thacher, and Breffle, 2005). Both on theoretical and practical grounds, however, latent class analysis is a promising approach to the study of social capital.

We can provide a more formal definition of our approach by noting that, in generalized linear models, explanatory variables, represented by a vector $\mathbf{x}$, influence individual's i response Y_i through a linear predictor $v_i = \mathbf{x}_i^{'}\boldsymbol{\beta}$. For dichotomous responses, the conditional probability of response 1 can be modeled as a logistic regression:

$$P(Y_i = 1 \mid v_i) = \frac{\exp(v_i)}{1+\exp(v_i)}. \qquad (1)$$

To analyze responses that measure aspects of social capital, we expand this model by assuming individuals belong to one of S unknown classes s = 1,…, S. The unconditional probability is modeled as a finite mixture of S unknown classes:

$$P(Y_i = 1) = \sum_{s=1}^{S} P(X = s) P(Y_i = 1 \mid X = s), \qquad (2)$$

where:

$$P(Y_i = 1 \mid S = s) = \frac{\exp(v_{is})}{1+\exp(v_{is})} \qquad (3)$$

This model is called a generalized linear finite-mixture model. In particular, let i = 1,…, I, denote the respondents. For each individual we observe the response to a set of 18 questions denoted k =1,…, 18. Then, $Y_{ik} = 1$ if the individual responds "yes" to question k, and $Y_{ik} = 0$ otherwise. The response pattern of an individual is represented by the vector, Y_i . Under a generalized finite-mixture model, we assume a finite number of social capital classes denoted s = 1,…, S. The discrete latent variable X represents the social capital class. Then:

$$P(Y_i) = \sum_{s=1}^{S} P(X_i = s) \times \prod_{k=1}^{18} P(Y_{ik} \mid X_i = s). \qquad (4)$$

The conditional probability that an individual in latent class s responds "yes" to indicator k is modeled as a logit equation:

$$P(Y_{ik} = 1 \mid X_i = s) = \frac{\exp(\beta_{ks})}{1+\exp(\beta_{ks})}, \qquad (5)$$

where β_{ks} is a free parameter. It is possible to include observed variables to predict class membership. We estimate models that include year dummy variables so that the probability of an individual belonging to a particular class depends on the year the responses were obtained. This modeling is similar to a fixed-effects approach. Let $\mathbf{z}_i$ be a vector of year dummies. Then, the conditional probability is:

$$P(Y_{ik}=1\,|\,\mathbf{z}_i, X_i=s)=\frac{\exp(\beta_{ks}+\sum_{t=1}^{T}\beta_{kt}z_{it})}{1+\exp(\beta_{ks}+\sum_{t=1}^{T}\beta_{kt}z_{it})}. \qquad (6)$$

We discuss the structure of the latent classes by comparing conditional response probabilities for each indicator given latent class membership. In addition, we calculate posterior probabilities using Bayes theorem:

$$P(X_i=s\,|\,Y_i)=\frac{P(X_i=s)\prod_k P(Y_{ik}\,|\,X_i=s)}{\sum_{s'} P(X_i=s')\prod_k P(Y_{ik}\,|\,X_i=s')}. \qquad (7)$$

After calculating posterior probabilities, we assign each individual to the latent class for which she has the highest posterior probability (empirical Bayes modal classification rule). The resulting characterization of each individual as belonging to one of *S* classes constitutes our typology of social capital.

Although equation (4) implies responses to the indicators are independent given latent class membership, it is possible to relax this assumption of local independence by including direct effects, that is, by combining any pair of dichotomous variables into one item and modeling the four potential response patterns (0,0), (1,0), (0,1), and (1,1), as one multinomial response (Skrondal and Rabe-Hesketh, 2004). For example, if we want to model a direct dependency between item 2 and item 3, we modify equation (5) as follows:

$$P(Y_{i2}=1, Y_{i3}=1\,|\,X_i=s)=\frac{\exp(\beta_{2s}+\beta_{3s}+\beta_{23s})}{1+\exp(\beta_{2s}+\beta_{3s}+\beta_{23s})}. \qquad (5')$$

To identify the need for direct effects we use bivariate residuals: Pearson chi-squared statistics divided by the degrees of freedom. For each pair-wise combination of indicators, this statistic compares the expected counts obtained by the estimated model to the actual counts in a two-way table. Large residuals indicate that the model cannot explain well the observed association between those two indicators. The typical strategy is to estimate the models under the assumption of local independence (and with year dummies as covariates) and select among the models that fit the data using information criteria. Then we relax the assumption of local independence for the selected model by including direct effects.

The parameters of the models are estimated using maximum likelihood with the likelihood function that is derived from the unconditional probability in equation (2). Several programs are available to estimate latent class models; we use Latent GOLD.

A common problem estimating latent class models is the presence of local maxima. To address this problem, we estimated each model 10 times with 10 different starting values. For the selected model, we found two maxima and the solution with the largest log-likelihood appeared 7 times. We use this solution to obtain the latent classes. In order to evaluate the goodness-of-fit of the models, we use the Pearson statistic that compares the observed frequencies of the response patterns to the expected frequencies of the model.[3] Because of sparse tables, we apply bootstrapping to calculate the Pearson statistic.[4] We estimate each model for 500 replication samples using maximum likelihood estimates as starting values. We reject the model if the bootstrap p-value of the Pearson statistic is smaller than .05 (Eid, Langeheine, and Diener, 2003). To select among models that cannot be rejected using the Pearson statistic, we use the minimum Bayesian information criterion (BIC) rule to select a model. The criterion is based on the log-likelihood of the model (LL) and accounts for the number of observations N and parameters to be estimated: BIC = -2LL + (logN)Npar.[5]

3 Results of Latent Class Models

We apply latent class analysis to the responses to 18 indicators by 14,527 individuals. Table 1 summarizes the 18 indicator variables. We choose our sample to be identical to

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[3] The Pearson statistic is usually defined as $\sum_j (n_j - e_j)^2 / e_j$ where *n* is the observed frequency of pattern *j* and *e* is the expected frequency. The statistic is asymptotically distributed as a χ^2 distribution with degrees of freedom equal to the number of response patterns minus the number of estimated parameters minus the number of categories.

[4] Sparse tables occur when small and zero observed frequencies are common. With sparse tables, fit statistics such as the Pearson statistic or the likelihood-ratio test cannot be guaranteed to follow the assumed χ^2 distribution.

[5] We also computed the Akaike information criterion (AIC = -2LL+2*Npar) and the consistent Akaike information criterion (CAIC = -2LL+[log(N)+1]*Npar). The AIC favors models with larger number of classes, a tendency that increases with the sample size. The CAIC favors models with fewer classes but this under-fitting declines with sample size. In our application, both the BIC and the CAIC indicate a model with seven latent classes is the best among the models that fit the data.

that used by Glaeser, Laibson, and Sacerdote (2002), henceforth referred to as GLS, so that later we can compare results.[6] GLS argue that because all of these variables are correlated, it is acceptable to choose a subset of them as a measure of social capital; their primary measure is the number of voluntary groups to which an individual belongs. Latent class models allow us to use trust and fairness in addition to voluntary group membership to generate a typology of social capital.

Because the data contain multiple cross-sections from the GSS, we allow the probability that an individual is assigned to a particular social capital class to depend on the year the individual responded to the survey.[7] Table 2 presents fit statistics from the latent class models assuming from one to nine groupings. We present each model's log-likelihood, the associated BIC, number of parameters, and bootstrapped p-value of the Pearson statistic. Using the bootstrap p-value, we find that models with fewer than 6 classes can be rejected. The minimum BIC rule indicates that the best model uses 7 classes. Once we selected a model with 7 classes, we relaxed the assumption of local independence. We modeled the responses to the indicators with the largest bivariate residual as a joint response and estimated the model. We repeated this process until the last direct effect was not statistically significant at the 5 percent level.[8]

Table 3A presents class sizes (as a proportion of the total sample) and the conditional response probabilities for each indicator given latent class membership. To construct the class size measures displayed in the first row of Table 3A, we calculate the probability of membership in each class for each individual and assign them to the class for which they have the highest probability. In addition, by observing the differences in response patterns we can differentiate between latent classes. We discuss below the characteristics of each class and provide a summary of these characteristics in Table 3B.

Class 1, the largest class (about 41 percent of the sample), corresponds to individuals with very low probabilities of membership in any type of voluntary

[6] We thank Bruce Sacerdote for graciously supplying the data.

[7] The samples were taken in 1975, 1978, 1980, 1983, 184, 1986, 1987 through 1991, 1993, and 1994.

[8] We include a total of eight direct effects. Membership in church organizations and membership in labor unions as well as membership in church organizations and membership in sport clubs show a negative correlation. The other six local dependencies show a positive correlation between sport and labor unions, youth clubs and sport clubs, school groups and youth clubs, hobby and sport clubs, school fraternities and fraternal organizations, and literary and hobby clubs. These direct effects are statistically significant at the 1 percent level.

organization as well as by low probabilities of FAIR and TRUST. Arguably, these individuals have low levels of social capital. Compared to individuals in latent Class 1, respondents in Class 2 are much more likely to state they trust other people and believe other people are fair than individuals in Class 1. When we calculate descriptive statistics by class, we find that individuals in Class 1 and 2 belong on average to .60 and .64 organizations, respectively, but in Class 1 only 38 percent of individuals believe people are fair and none state people can be trusted while in Class 2, 80 percent of the individuals believe other people are fair and 99 percent claim others can be trusted. Therefore, measures that simply tabulate group membership to proxy for social capital would not be able to distinguish between individuals in Class 1 and 2.

Individuals in Class 3 have higher probabilities of FAIR and TRUST than individuals in any other class but Class 2. In addition, the probability that an individual assigned to Class 3 belongs to a professional organization is relatively high, 56 percent. Individuals in Class 4 also have high probabilities of FAIR and TRUST but are not as likely to belong to any type of organization except a church group (almost 76 percent probability). Among all individuals in the sample, individuals in Class 5 have the largest probabilities of belonging to unions, veteran, and fraternal groups (39, 34, and 39 percent respectively). Individuals in Class 6 have very low probabilities of FAIR and TRUST but, unlike Class 1, a relatively high probability of belonging to a church organization (around 52 percent) and between 20 percent and 30 percent probability of belonging to a youth organization, school organization, sport group, and professional organization.

Class 7, the smallest class with 4 percent of the individuals in the sample, corresponds to individuals with large amounts of social capital, with high probabilities of group membership as well as high probability of trusting others. Individuals in Class 7 are the most likely to belong to all types of organizations except veterans groups, unions, fraternal organizations, and nationality groups. In addition, individuals in this class have fairly high probabilities of stating other people can be trusted and people are fair. The average number of memberships in this latent class is 7.04 (with a standard deviation of 1.75 groups). By most measures, Class 7 would be characterized by high levels of social capital though it is the smallest group we have identified.

Three conclusions are particularly worth noticing from the results above. First, FAIR and TRUST help to distinguish individuals across classes in a nontrivial manner. Although in the literature on social capital it is often assumed that trust is a consequence of social networks, we find that there are individuals who are very likely to express trust of others but are unlikely to belong to any voluntary organization (individuals in Class 2). On the other hand, we find that some individuals who are likely to belong to church and other groups are not necessarily stating other people are fair and can be trusted (individuals in Class 6).

Second, individuals with the same number of memberships are sorted into different types of social capital. For example, of all individuals with three memberships who trust others and believe people are fair, 20 percent are classified in latent Class 2, 32 percent in Class 3, and 34 percent in Class 4. Similarly, individuals in Class 3 have the highest probability of belonging to a professional organization, individuals in Class 4 have relatively high probabilities of belonging to church and sports groups, while individuals in Class 5 have relatively high probabilities for belonging to veterans groups and unions. Thus, in spite of the fact that all the individuals in these classes belong to about three groups, their social networks are arguably different. A key dimension along which membership in these groups differ is that they may require different levels of involvement of time and/or money. The importance of this last observation will become apparent when we discuss the determinants of social capital formation.

Finally, examining the average number of group memberships by class also reveals that a simple ordering of classes by number of memberships does not necessarily provide a meaningful measure of social capital. For example, it is difficult to claim that individuals in Class 6 have more social capital than individuals in Class 3. The results of the latent class model suggest that it is more appropriate to say that individuals in Class 6 have a different type of social capital than individuals in Class 3.

Table 4 presents the estimates of the β parameters in equation 5. We use dummy coding for identification where the reference class is Class 1, the class with low probabilities of considering other people to be fair, trustworthy and of membership in any kind of group. A positive (negative) estimate for class s means that an individual in class s is more (less) likely to answers "yes" to the indicator than an individual in Class 1. In order to compare the magnitude of the effects we can calculate the exponential value of the estimate and interpret the result as the odds of answering “yes” in class *s* relative to the reference class. For example, the probability of membership in a church organization is approximately 3.4 (or $e^{1.22}$) times higher in Class 2 than in Class 1; while the probability of membership in a church organization is more than 15 times higher in Class 4 than in Class 1. Table 4 also presents Wald statistics and p-values for the null hypothesis that each estimate for a given indicator equals zero. In this model, we can strongly reject the null hypothesis for the 18 indicators. Thus, all indicators discriminate between classes in a statistically significant manner.

Table 5 presents the effects of year dummies. The omitted year is 1994. The results indicate that the year dummies influence significantly latent class membership only for 1975, 1978, 1980, and 1984. Compared to respondents in 1994, individuals who took the survey in 1975 and 1978 are twice as likely to be in Class 4 than in Class 1. Compared to respondents in 1994, individuals who took the survey in 1980 and 1984 are twice as likely to belong to Class 2 than to Class 1. These results suggest that, relative to the most recent year of data in the sample, respondents in 1975, 1978, 1980, and 1984 are more likely to be in classes with high conditional probabilities for FAIR and TRUST than in the no social capital class. All other effects on the odds are not particularly large. These results provide some supporting evidence for the claim made in Putnam (2000) that the amount of social capital held by Americans is declining, at least to the extent that social capital can be approximated by trust.[9]

4 Using Latent Classes to Study Social Capital Formation

In the previous section, we explained and demonstrated the construction of latent classes that measure an individual’s social capital using GSS data. We argued that the classes we constructed provided a typology of social capital that capture the idea of networks embedded in the concept of social capital better than proxy variables such as trust or number of group memberships. In this section, we demonstrate the importance of these differences by showing that the use of latent classes allows meaningfully different

[9] See Paxton (1999) for a thorough analysis of Putnam’s claim. Our results are consistent with Paxton’s finding that trust in individuals, but not degree of association, has declined in the United States.

conclusions and new insights about the formation of social capital at the individual level. Specifically, we start with the theory developed by GLS and compare their empirical results to results we obtain using latent class models.

GLS develop a model of social capital accumulation in which individuals invest time to accumulate social capital. Some of the key predictions of their model are that social capital investment declines with the opportunity cost of time, declines with age, declines with mobility to different locations, increases with the occupational returns to social skills, and is larger in communities with more aggregate social capital. Using the number of group memberships as a proxy for social capital, they are able to find empirical evidence consistent with many of their model's predictions. However, there are two key predictions for which they are unable to find evidence. First, they find only a positive association between income and group membership, contrary to their model that predicts that higher wages should be associated with less social capital accumulation because of the higher opportunity cost of accumulating it. Second, they are unable to find evidence that social capital correlates within peer groups. In this section, we use the same data that GLS analyze and our typology of social capital to show new meaningful results that are consistent with the theory developed by GLS and enrich the discussions of the determinants of social capital.

We use the same independent variables used by GLS (descriptive statistics are presented in Table 6) and present the coefficients from this estimation in Table 7. The specification reported in Table 7 closely resembles a base specification of GLS in which they investigate how demographic characteristics are associated with the number of group memberships.[10] Although GLS estimate OLS and IV models, we use a multinomial logistic regression because class membership is qualitative and unordered. Before discussing the results of the multinomial logit model, it is worth noticing that Hausman tests strongly reject the null hypothesis that any of the categories, that is, the latent classes, can be collapsed and that all categories are indistinguishable with respect to the independent variables in the model, giving support to the idea that the types of

[10] We report results of only one of the several GLS specifications. We receive qualitatively similar results for all other specifications reported in GLS.

social capital we identified using latent class analysis are distinct and economically meaningful.[11]

Examined directly, the coefficients in Table 7 have limited interpretive value. Therefore, in Table 8, we report the change in the odds ratio that results from a one standard deviation increase in the independent variable. For example, the first row of column 3 indicates that the odds ratio of being in Class 1 vs. 2, $\frac{P(class1)}{P(class2)}$, is .58 times larger when education increases by one standard deviation. In other words, higher education levels reduce the probability of being in Class 1 relative to Class 2. Similarly, the first row of column 5 indicates that $\frac{P(class1)}{P(class2)}$ is 1.41 times larger when the variable Black is increased by one standard deviation, suggesting that being black is associated with a higher probability of being in Class 1 relative to Class 2. As can be seen from these examples, cells in which the change in the odds ratio is less than one indicate a reduced probability of being in the class in column 1 relative to the class in column 2, while a change in the odds ratio that is greater than one indicates that the probability of being in the class in column 1 has increased relative to the probability of being in the class in column 2.[12] In Table 8, we report only changes that are significant at the 5 percent significance level. Insignificant changes are associated with blank cells in the table.

The results in Table 8 indicate how individual-specific characteristics sort people into different types of social capital. Some particularly interesting comparisons are between Class 1 and Class 2 or between Class 1 and Class 6. For example, the odds comparing Class 1 (low membership, low trust group) and Class 2 (low membership, high trust group) indicate that individuals with high levels of education and income are less likely to be in Class 1 than in Class 2, while being black or female or over the age of 49 are associated with higher probabilities of being in Class 1 relative to Class 2.

[11] A Hausman test also confirms that the assumption of the independence of irrelevant alternatives is valid.

[12] These changes are calculated directly from the coefficients in Table 7. For example, the Class 2 – Class 3 comparison in Table 8 for the variable education (column 3, row 7) is $e^{change\,in\,b * std(education)}$ where the change in b is the difference between the coefficients for education for classes 2 and 3 in Table 7. In other words, with a standard deviation for education of 3.15, the change in the odds ratio reported in Table 8 is $e^{(.1710-.6083)*3.15}$=.25.

Looking at the comparison between Class 1 and Class 6, we see that higher income and education are associated with higher probabilities of being in Class 6 (low trust, relatively high membership) relative to Class 1 (low trust, low membership), but being married and younger increase the probabilities of being in Class 1.

Comparing among classes 3, 4, and 5, we see that, perhaps not surprisingly, women are much more likely to be in Class 3 than Class 5 (recall that Class 5 had much higher probability of belonging to a veterans group or a union). Education has also a strong substantive effect: individuals with higher levels of education are much more likely to be in Class 3 (the class with high conditional probability of membership in professional groups) than in classes 4, 5, or 6. This finding is particularly interesting because, in terms of number of memberships, these classes are fairly similar. Thus, an overall point to make about the results in Table 8 is that there are many socio-economic determinants that sort individuals into different types of social capital classes that have very similar average group memberships.

Our results can also speak to the commonalities between the classes. For example, individuals in both classes 1 and 6 have low values of TRUST and FAIR. The results in Table 8 suggest that one demographic characteristic that sorts individuals into these two "low-trust" classes is being black. Interestingly, however, this same demographic characteristic also sorts people into class 7, the high social capital class, vs. classes 2, 3, or 4.

One of the hypotheses GLS obtain from the theoretical model is a negative association between social capital and income: if individuals with high incomes have a high opportunity cost of time, then we should find that high-income individuals belong to few groups. However, GLS find that, contrary to the implications of the model, there is a positive association between social capital and income. Our typology of social capital sheds some light on this issue. In particular, we note that some voluntary groups have high time commitments but low monetary costs (e.g., church or sport groups) while other groups (e.g., professional associations) have relatively low time commitments and high monetary costs in the form of membership fees. If individuals do take into account the opportunity cost of their time when accumulating social capital, then we should see that higher-income individuals should be more likely to join social networks with lower time commitments but higher monetary costs. Our results support this conjecture. When we compare classes 3, 4, and 5, we see that the odds that individuals are in Class 3, the class with the highest probability of professional memberships, rather than in Class 4 or Class 5 increase with income. Furthermore, the probability of being in Class 4, the class described by high probabilities of being in a sports or church group, declines with income. These results are consistent with the fact that individuals consider the opportunity cost of their time in decisions regarding social capital accumulation, a result that is impossible to uncover simply using number of group memberships as a measure of social capital.[13] These results are also broadly consistent with the argument in Skocpol (2003) that elite Americans have shifted the burden of civic engagement toward managed professionally-staffed organizations.

We turn now to another prediction of the theory that GLS were unable to support empirically—specifically, that the social capital of individuals should be positively correlated with the social capital of their peer group because of interpersonal complementarities in social capital accumulation. GLS are unable to document a statistically significant relationship between the number of memberships of an individual and the average number of memberships in that individual's peer group. However, we are able to find evidence for these interpersonal complementarities in social capital accumulation using our measure of social capital.

Specifically, following GLS, we define an individual's peer group by geographic location (primary sampling unit) and religion. For example, a peer group might be Baptists in Memphis or Catholics in Cleveland. Then, we calculate the average probability of membership in each class for that individual's peer group, excluding the specific individual from the calculation and dropping any observations for which there are less than five people in a peer group. We then use the average probabilities of membership for the individual's peer group as an explanatory variable. Now, the probabilities of peer group membership in each class vary by both individual and class. In other words, for each individual there will be a separate probability of peer group membership associated with each class, in contrast to the other independent variables

[13] Of course, like GLS, we can only comment on probabilities and cannot make a statement about causation. We simply point out that our findings are at least consistent with a theory of social capital accumulation that takes into account the opportunity cost of time.

(e.g., age, education, income, etc.) that do not vary by class for each individual. Therefore, rather than estimating a multinomial logistic regression, we must estimate a conditional logistic regression.

An additional econometric concern is the potential that omitted variables might create a spurious correlation between peer group values and individual values. We follow GLS and instrument for the probabilities of peer group membership with the average education, age, marital status and income of the peer group. (In this estimation the standard errors are bootstrapped.) Unlike GLS, however, even after employing instrumental variables estimation we still find significant effects of the peer group effects, indicating that there are interpersonal complementarities in social capital accumulation.

Table 9 displays the results of the conditional logit model. Note that in the conditional logit model we estimate six coefficients for the individual-specific variables (education, income, and so on) but only a single coefficient for the class-specific variable (average class-membership probability). The positive and statistically significant effect of the class-membership probability for peer group provides evidence that interpersonal complementarities in social capital accumulation do exist. We believe that our stronger empirical results are a direct consequence of our improved definition of social capital that considers not just the number of groups, but the types of networks to which individuals belong.[14]

5 Conclusions

In this paper we motivate and demonstrate the use of latent class models to measure social capital. The empirical treatment of social capital that we propose links more closely the measurement of social capital with the concepts of social networks that underlie it. Latent class analysis treats different kinds of social capital as being qualitatively different and is consistent with an interpretation of social capital as an unobservable multidimensional construct. Furthermore, we show that this new treatment

[14] The specification reported in Table 9 does not include state dummies because including them does not allow the maximum likelihood estimation to converge. GLS do include state dummies in the IV estimations they report. However the inclusion of state dummies is not driving the results: when we exclude state dummies from the IV specification reported in GLS, we do not find materially different results for the coefficient on peer memberships. Thus, the difference in results is not attributable to the exclusion of state dummies.

generates empirical results consistent with a theory of social capital accumulation that the standard treatment of social capital could not reveal. We replicate the models in Glaeser, Laibson, and Sacerdote (2002). While Glaeser, Laibson, and Sacerdote measure social capital as the number of voluntary organization memberships individuals hold, we use latent class analysis to classify individuals into distinct types of social capital using both memberships and indicators of trust and fairness. Using the same data, we find peer-group effects that could not be identified previously. We also find results consistent with the hypothesis that individuals with high opportunity cost of time choose networks with relatively low time commitment and perhaps high monetary cost. Finally, we find that socio-economic determinants sort individuals into types of social capital that vary in the nature of the social network but not necessarily in the number of memberships forming the network.

This paper has focused on the accumulation of social capital at the individual level. We note that the typology of social capital we obtain from latent class models can also be used as an independent variable by entering a series of dummy variables indicating class membership. In addition, these methods could be extended to create aggregate data by examining the proportions of individuals that make up each class to explain the importance of social capital at the country level. In doing so, it would be important to consider the distribution of social capital as well—a highly fractionalized society with many different classes suggests that any one individual cannot have a great deal of social capital. Because fewer classes suggest fewer different social networks, the potential to accumulate social capital in these societies may be greater. A second approach to examine social capital at the country level would be to perform multilevel latent class models that derive simultaneously both country and individual segments based on individual-level responses (Vermunt, 2003). Research generating macro-level measures of social capital is currently in progress.

Table 1: Indicators (N = 14,527)

Indicator	Description	Percent
Fair	= 1 if "people are fair" (= 0 if "people try to take advantage")	59.72
Trust	= 1 if people can be trusted	39.87
Church	= 1 if membership in church organization	34.58
Service	= 1 if membership in service group	9.72
Veteran	= 1 if membership in veteran group	7.04
Union	= 1 if membership in labor union	13.20
Political	= 1 if membership in political club	3.97
Youth	= 1 if membership in youth group	9.48
School	= 1 if membership in school service	13.08
Farm	= 1 if membership in farm organization	3.71
Fraternal	= 1 if membership in fraternal group	9.40
Sport	= 1 if membership in sports club	19.50
Hobby	= 1 if membership in hobby club	9.31
Greek	= 1 if membership in school fraternity	4.80
Nationality	= 1 if membership in nationality group	3.30
Literary	= 1 if membership in literary or art group	8.78
Professional	= 1 if membership in professional society	14.70
Other	= 1 if membership in any other group	10.43

Table 2: Model Selection: Fit Statistics

	LL	BIC(LL)	Npar	p-value of Pearson statistic
1 Class	-94204.2209	188580.9495	18	<.001
2 Classes	-89483.0706	179435.7456	49	<.001
3 Classes	-88436.1251	177638.9513	80	<.001
4 Classes	-88044.7586	177153.3151	111	<.001
5 Classes	-87753.8485	176868.5916	142	.004 (.0028)
6 Classes	-87529.3428	176716.6768	173	.030 (.0076)
7 Classes	-87328.8866	176612.8611	204	.162 (.0165)
8 Classes	-87213.3294	176678.8434	235	.188 (.0175)
9 Classes	-87108.0368	176765.3549	266	.272 (.0199)
7 Classes with 8 local dependencies	-87038.8559	176087.4698	212	.200 (.018)

Table 3A: Conditional Response Probabilities

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Class Size (based on modal assignment)	.4136	.1945	.1128	.1062	.0620	.0704	.0405
Individuals	6,008	2,825	1,639	1,543	901	1,023	588
Fair	0.3235	0.8113	0.9020	0.8681	0.6906	0.0087	0.7974
Trust	0.0095	0.7696	0.7571	0.5209	0.5217	0.0142	0.6038
Church	0.1853	0.1564	0.4082	0.7583	0.3564	0.5248	0.8018
Service	0.0052	0.0001	0.1939	0.0977	0.2085	0.1741	0.6364
Veteran	0.0251	0.0288	0.0369	0.0394	0.3869	0.1082	0.1692
Union	0.1185	0.1021	0.0972	0.0943	0.3389	0.1596	0.1685
Political	0.0021	0.0035	0.0709	0.0289	0.0791	0.0762	0.3002
Youth	0.0135	0.0060	0.1066	0.2275	0.0746	0.2636	0.4751
School	0.0356	0.0342	0.2300	0.2671	0.0139	0.3008	0.5607
Farm	0.0112	0.0167	0.0184	0.0875	0.0680	0.0601	0.1485
Fraternal	0.0191	0.0324	0.1345	0.0596	0.3885	0.1186	0.3635
Sport	0.0807	0.0989	0.3309	0.2826	0.2086	0.3905	0.5398
Hobby	0.0209	0.0332	0.1613	0.1485	0.1214	0.2057	0.3334
Greek	0.0007	0.0121	0.1605	0.0065	0.0198	0.1039	0.3203
Nationality	0.0078	0.0057	0.0625	0.0260	0.0423	0.0786	0.1922
Literary	0.0058	0.0111	0.2319	0.1119	0.0159	0.1828	0.5515
Professional	0.0205	0.0584	0.5647	0.0260	0.0559	0.2467	0.6487
Other	0.0504	0.0869	0.1498	0.1566	0.1223	0.1476	0.2118
Average number of group memberships (standard deviation)	0.60 (0.70)	0.64 (0.68)	3.14 (1.26)	2.84 (1.04)	3.00 (1.11)	3.56 (1.42)	7.04 (1.75)

Table 3B: Qualitative Characteristics of the Classes

Class	Characteristics
Class 1	Low probabilities of FAIR and TRUST and low probabilities of group membership. By most measures of social capital, people in class 1 would be considered to have low social capital.
Class 2	High probabilities of FAIR and TRUST and low probabilities of group membership.
Class 3	High probabilities of FAIR and TRUST. Relatively high probabilities of memberships in professional organizations and church groups.
Class 4	High probabilities of FAIR and TRUST. Relatively high probabilities of memberships in church groups. Relatively low probabilities of membership in youth, school and sports groups.
Class 5	High probabilities of FAIR and TRUST. Largest probabilities of memberships in unions, veterans, and fraternal groups.
Class 6	Low probabilities of FAIR and TRUST. High probability of membership in a church group and relatively low probability of membership in school and sports groups.
Class 7	High probabilities of FAIR and TRUST. Largest membership probabilities for all groups except veterans, unions, and fraternal organizations. By most measures of social capital, people in class 7 would be considered to have high social capital.

Table 4: Parameter Estimates for Indicators*

	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Wald	p-value
Fair	2.1965	2.9576	2.6219	1.5410	-3.994	2.1081	254.2726	5.0e-52
Trust	5.8546	5.7858	4.7324	4.7355	0.4064	5.0702	82.3532	1.2e-15
Church	-0.202	1.2156	2.7252	0.9957	1.7332	3.1161	602.8167	5.8e-127
Service	-3.903	3.8205	3.0219	3.9115	3.6887	5.8053	322.1396	1.5e-66
Veteran	0.1424	0.3984	0.4670	3.2010	1.5526	2.0700	357.3839	4.0e-74
Union	-0.1845	-0.3104	-0.2360	1.3186	0.2588	0.3178	150.3091	6.7e-30
Political	0.5034	3.5919	2.6494	3.7109	3.6701	5.3187	263.3275	5.8e-54
Youth	-0.8502	1.5451	2.5347	1.6429	2.5788	3.1477	178.8749	5.9e-36
School	-0.0265	1.9633	2.0031	-1.0812	2.1313	3.0408	425.4804	9.3e-89
Farm	0.4059	0.5061	2.1384	1.8653	1.7338	2.7366	170.8837	2.9e-34
Fraternal	0.5184	1.8300	1.1668	3.4617	1.7662	2.9887	403.8265	4.2e-84
Sport	0.2293	1.6816	1.4558	0.9346	1.7724	2.2572	289.3706	1.5e-59
Hobby	0.4624	1.8972	1.9179	1.8012	2.2138	2.5536	197.3525	6.9e-40
Greek	2.9034	5.5120	2.2255	2.8814	5.0223	6.1608	186.8986	1.2e-37
Nationality	-0.3137	2.1391	1.2244	1.7289	2.3860	3.4114	274.4583	2.4e-56
Literary	0.6414	3.8382	2.9641	0.9235	3.4987	5.1465	406.1928	1.3e-84
Professional	1.0891	4.1293	0.2443	1.0427	2.7530	4.4826	708.7377	7.9e-150
Other	0.5837	1.2003	1.2529	0.9658	1.1826	1.6223	159.0193	9.6e-32

*Reference group is Class 1 (no social capital class). A positive (negative) estimate means that individuals in that class are more (less) likely to respond affirmatively to the corresponding indicator than individuals in Class 1.

Table 5: Parameter Estimates for Covariates, Year Dummies*

Covariates	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Wald	p-value
1975	0.3231	-0.4509	0.7082	0.0267	-0.4127	-0.1367	16.2919	0.012
1978	0.2381	-0.1135	0.7316	-0.1286	-0.4559	-0.4848	15.9180	0.014
1980	0.7914	-0.1712	0.1037	0.2666	-0.2070	-0.2902	23.0640	0.00078
1983	0.0070	-0.0537	0.5058	0.0237	0.1996	-0.2287	3.6904	0.72
1984	0.7297	0.1233	0.3283	0.1854	-0.2687	0.1486	16.9302	0.0095
1986	0.1016	-0.0090	0.8367	-0.3011	-0.0524	-0.1786	10.3173	0.11
1987	0.2463	-0.4007	-0.1234	-0.2985	-0.1816	-0.5049	11.2087	0.082
1988	0.0679	-0.0236	0.3935	0.0657	-0.2061	-0.4531	4.8706	0.56
1989	0.2774	0.2301	0.2347	-0.1056	-0.0535	-0.3999	5.1187	0.53
1990	0.0779	-0.0797	0.4282	0.1878	-0.0708	0.2843	2.3091	0.89
1991	0.2027	0.0480	0.3947	-0.5406	-0.1177	-0.5987	8.8637	0.18
1993	-0.0537	0.1173	0.4109	-0.4323	0.2286	-0.0496	4.4589	0.61

*Reference group is Class 1 (no social capital class); reference year is 1994.

Table 6: Descriptive Statistics For Independent Variables

Variable	Definition	Mean	Std. Dev.
Education	Years Education	12.39	3.15
Log Income	Log Annual Income	2.09	0.65
Income Missing	=1 if income not provided	0.04	0.20
Black	=1 if black	0.14	0.34
Female	=1 if female	0.56	0.50
Birth Year	Year of birth	1940.18	18.28
Married	=1 if married	0.57	0.50
Babies	=1 if have young children	0.26	0.59
Preteen	=1 if have preteens in household	0.32	0.69
Teens	=1 if have teenagers	0.24	0.59
South	=1 if in south	0.34	0.47
East	=1 if in east	0.20	0.40
West	=1 if in west	0.19	0.39
Log of Population	= log of population in PSU	3.43	2.17
Age 18-29	=1 if between 18 and 29	0.24	0.43
Age 30-39	=1 if between 30 and 39	0.23	0.42
Age 40-49	=1 if 40 to 49	0.16	0.37
Baptist	=1 if Baptist	0.21	0.41
Methodist	=1 if Methodist	0.10	0.30
Lutheran	=1 if Lutheran	0.07	0.25
Presbyterian	=1 if Presbyterian	0.05	0.21
Episcopalian	=1 if Episcopalian	0.02	0.15
Other Protestant	=1 if belong to other Protestant religion	0.14	0.35
Non Denominational Protestant	=1 if non-denominational Protestant	0.04	0.19
Jewish	=1 if Jewish	0.02	0.13
Catholic	=1 if Catholic	0.25	0.43
Other Religion	=1 if other religious affiliation	0.02	0.14

Total observations used in estimations: 13,926.

Table 7: Multinomial logistic regression for class membership

	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Education	.1710** (.0104)	.6083** (.0149)	.2306** (.0135)	.1530** (.0155)	.3123** (.0160)	.6263** (.0205)
Log Income	.1947** (.0586)	.6225** (.1037)	.4069** (.0853)	.7566** (.1256)	.2609** (.0871)	.6308** (.1591)
Income Missing	.4505** (.1675)	.5007 (.3470)	.7654** (.2388)	1.361** (.3489)	.6876** (.2544)	1.381** (.4447)
Black	-1.004** (.0975)	-1.322** (8.73)	-.8539** (.1208)	-.3625** (.1559)	.1549 (.1073)	-.0985 (.1761)
Female	-.1048** (.0504)	.0878 (.0678)	.3595** (.0658)	-1.478** (.0880)	-.1078 (.0734)	.1387 (.0995)
Birth Year	-.0215** (.0032)	.0028 (.0047)	-.0197** (.0041)	-.0263** (.0047)	.0182** (.0052)	-.0244** (.0063)
Married	.0708 (.0560)	-.0767 (.0764)	.2527** (.0726)	.0583 (.0932)	-.1969** (.0824)	-.1114 (.1104)
Age 18-29	.3189** (.1438)	-.4764** (.1971)	.0002 (.1820)	-1.209** (.2411)	-.4526** (.2190)	-.0232 (.2766)
Age 30-39	.2891** (.1228)	-.3350** (.1653)	-.0220 (.1515)	-.5446** (.1899)	-.4334** (.1838)	-.2221 (.2301)
Age 40-49	.3448** (.1021)	.0349 (.1364)	.1386 (.1255)	-.1374 (.1511)	-.1703 (.1559)	-.1349 (.1925)

Base category is Class 1. Estimated with 13,926 observations. Standard errors are in parentheses. **significant at the 5% level, *significant at the 10% level. Estimations also include, state dummies, dummies for religious affiliation, regional dummies, log of population, and dummy variables for babies, preteens, and teens in the household.

Table 8: Change in Odds Ratio for a one standard deviation increase in independent variable

Odds Comparing Column 1 – Column 2		(3) Education	(4) Log Income	(5) Black	(6) Female	(7) Married	(8) Age 18-29	(9) Age 30-39	(10) Age 40-49
(1) Column 1	(2) Column 2								
Class1	Class2	.58	.88	1.41	1.05		.87	.88	.88
Class1	Class3	.15	.67	1.58			1.22	1.15	
Class1	Class4	.48	.77	1.34	.84	.88			
Class1	Class5	.62	.61	1.13	2.08		1.68	1.26	
Class1	Class6	.37	.85			1.10	1.21	1.20	
Class1	Class7	.14	.66						
Class2	Class3	.25	.76	1.11	.90	1.08	1.40	1.30	1.12
Class2	Class4	.83	.87		.79	.91		1.14	
Class2	Class5		.70	.80	1.98		1.92	1.42	1.20
Class2	Class6	.64		.67		1.14	1.39	1.36	1.21
Class2	Class7	.24	.75	.73	.88			1.24	1.19
Class3	Class4	3.29	1.15	.85	.87	.85	.82		
Class3	Class5	4.20		.71	2.17		1.37		
Class3	Class6	2.54	1.26	.60	1.10				
Class3	Class7			.66					
Class4	Class5	1.28	.80	.84	2.49	1.10	1.68	1.24	
Class4	Class6	0.77		.71	1.26	1.25	1.21	1.19	1.12
Class4	Class7	.29		.77	1.16	1.20			
Class5	Class6	.61	1.38	.84	.51	1.13	.72		
Class5	Class7	.22			.45		.60		
Class6	Class7	.37	.79		.88				

Each cell gives the change in the odds ratio that results from a one standard deviation increase in the selected independent variable. The odds ratio is defined as the probability of belonging to the class in the Group 1 column divided by the probability of belonging to the class in the Group 2 column. Only changes that are significant at the 5 percent level are reported. Blank cells indicate the estimated change is not statistically significant.

Table 9: Conditional logistic regression for class membership

	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Membership probability of peer group	1.069** (.3869)	1.069** (.3869)	1.069** (.3869)	1.069** (.3869)	1.069** (.3869)	1.069** (.3869)
Education	.1722** (10.06)	.6160** (.0248)	.2399** (.0192)	.1525** (.0181)	.3068** (.0231)	.6149** (.0275)
Log Income	.1414 (.0924)	.5495** (.1574)	.3651** (.1147)	.5873** (.1539)	.2542** (.1124)	.5353** (.2463)
Income Missing	.4228 (.3211)	.3667 (.4308)	.6961** (.3151)	1.002** (.4343)	.7071* (.3946)	1.204** (.5950)
Black	-.9678** (.1274)	-1.294** (.1989)	-.8444** (.1878)	-.4801** (.2371)	.1680 (.1460)	-.1743 (.2293)
Female	-.1178* (.0703)	.1020 (1.03)	.3502** (.0853)	-1.411** (.1058)	-.1113 (.0858)	.0666 (.1301)
Birth Year	-.0199** (.0044)	.0033 (.0071)	-.0208** (.0058)	-.0258** (.0063)	.0156** (.0072)	-.0278** (.0078)
Married	.1061 (.0893)	-.0735 (.1436)	.2706** (.1141)	.1409 (.1343)	-.2246** (.1133)	-.0951 (.1233)
Age 18-29	.2924 (.2032)	-.4434* (.2696)	.0271 (.2772)	-1.144** (.2847)	-.3473 (.2827)	.1073 (.3160)
Age 30-39	.2710 (.1815)	-.3570 (.2466)	.0446 (.2009)	-.4862** (.2312)	-.3127 (.2542)	-.0962 (.2844)
Age 40-49	.3497** (.1513)	.0522 (.1818)	.1661 (.1942)	-.0004 (.1720)	-.1283 (0.58)	-.0437 (.2319)

Estimated via instrumental variables estimation. Bootstrapped standard errors are in parentheses. **significant at the 5% level, *significant at the 10% level. Estimations also include, dummies for religious affiliation, regional dummies, log of population, and dummy variables for babies, preteens, and teens in the household. Peer groups are defined as religion by primary sampling unit cell (e.g., Baptists in Memphis). Membership probability of peer group is the average probability of membership in a particular class for the individual's peer group, excluding the individual. Instruments for membership probability of peer group were average age, education, income and marital status for the peer group.

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