Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes

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Abstract

We use a novel dataset and research design to empirically detect the effect of social interactions among neighbors on labor market outcomes. Specifically, using Census data that characterize residential and employment locations down to the city block, we examine whether individuals residing in the same block are more likely to work together than individuals in nearby but not identical blocks. We find significant evidence of social interactions: the baseline probability of working together is 0.93% at the block level compared to 0.51% at the block group level (a collection of ten contiguous blocks). We also provide evidence as to which types of matches between individuals result in greater levels of referrals. These findings are robust to the introduction of detailed controls for socio-demographic characteristics and block group fixed effects, as well as across various specifications intended to address sorting and housing market rather than labor market referrals. Further, our estimated effects have a significant impact on a wide range of labor market outcomes more generally.

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1 Introduction

The relevance of social networks and local interactions for economic outcomes has been increasingly recognized by economists in a variety of contexts. Some recent examples include crime (Glaeser et al. (1996)); welfare program participation (Bertrand et al. (2000)); the diffusion of new technologies (Conley and Udry (2003), Bandiera and Rasul (2003)); peer effects in education (Sacerdote (2001), Zimmerman (2003), Zax and Rees (2002)); neighborhood effects (Case and Katz (1991), Aaronson (1998), Weinberg et al. (forthcoming)); knowledge spillovers and economies of agglomeration (Jaffe et al. (1993), Audretsch and Feldman (1996), Glaeser et al. (1992)).[1]

More specifically with respect to labor market activities, a growing literature both in sociology and economics has documented the widespread use of social networks in job search.[2] An early study of the Chicago labor market by Rees and Schultz (1970) finds that informal sources such as referrals from current employees accounts for about half of all white collar hires and for about four fifths of blue collar hires. Granovetter (1995) finds that roughly 56% of all new jobs are found through neighbors, friends, relatives, or business acquaintances. Corcoran et al. (1980) confirm this basic finding and report, in addition, that informal hiring channels are more prevalent among black workers, as well as younger and less educated workers.[3]

A related literature has studied the role of social interactions at the local level by exploiting the (quasi)-experimental nature of several programs aimed at residents of low-income urban neighborhoods. In Chicago in the late 1970's, the Gautreaux Program – as part of a court-imposed public housing de-segregation effort – gave housing vouchers to eligible black families in public housing to move to white or racially mixed neighborhoods. Popkin et al. (1993) find notable improvements in labor outcomes resulting from the relocation. More recently, the Moving To Opportunity demonstration (MTO) is a randomized experiment that gave Section 8 housing vouchers that allowed participants to move from high-poverty neighborhoods in five U.S. cities. Katz et al. (2001), using data from the Boston site, report improved health outcomes for adults and children, but no significant effects of the program on employment, earnings and welfare receipt of household heads; Ludwig et al. (2001) study the Baltimore site and find a significant reduction in juvenile crime following the relocation.[4]

[1] For a more extensive review of the literature, both theoretical and empirical, see Brock and Durlauf (2001) or Conley and Topa (2003).

[2] The use of informal methods in job search can be rationalized as a means to reduce the two-sided uncertainty regarding the quality of a prospective employer-employee match. Montgomery (1991) models the employer's side of the problem. Calvo-Armengol and Jackson (forthcoming) explicitly model the information exchange process within workers' networks.

[3] More recently, Addison and Portugal (2001) study data from Portugal and find that roughly half of their respondents found their current jobs using informal methods; Wahba and Zenou (2003) report a very similar incidence of informal search method by the unemployed using Egyptian data.

[4] Other research has used randomized experiments to look for evidence of social interactions in various settings: see Sacerdote (2001), Duflo and Saez (2003), Palacios-Huerta (2003).

In this paper, we follow a novel route to detect the effect of social interactions among neighbors on labor market outcomes, building on these previous studies in several ways.[5] First, with respect to the literature on informal hiring channels, we add the neighborhood dimension to the study of referrals in job search, thereby contributing to the debate on whether residential location affects access to opportunities. Further, in addition to just detecting the use of informal search methods, we provide evidence on the ultimate incidence of these methods on labor market outcomes, such as labor force participation, employment, hours worked and earnings.[6] The paper also builds on the neighborhood effects literature by providing a detailed analysis of a specific channel through which interactions at the neighborhood level may operate. A limitation of the existing literature is that it is necessarily agnostic as to the actual mechanisms linking neighborhoods to individual outcomes: a cursory list of potential mechanisms includes information exchanges about jobs, preference interdependence and social norms, neighborhood-wide enforcement, congestion effects and complementarities, environmental quality, school quality – to name but a few.

The basic idea of our paper is to examine whether individuals residing in the same neighborhood (to be defined more precisely later) are characterized by undue clustering of their work locations, suggesting the presence of local social interactions.[7] Suppose for the moment that space is continuous and homogeneous. A number of standard models would predict that the place of work of residents at a given location would be uniformly distributed along any given circle drawn around that residential location. On the other hand, suppose that unemployed workers use informal hiring channels in their job search, such as referrals from current employees at a given firm, and that agents interact more frequently with social contacts who reside physically close. Then the work locations of residents of a particular area will be no longer uniformly distributed around that neighborhood, but rather they will be tend to be geographically clustered. Thus a simple test for the presence of informal local hiring channels is to see whether agents who live close to each other also tend to work together.

Of course, a host of potential problems immediately come to mind. Perhaps the

[5] Topa (2001) aims at empirically quantifying the magnitude of local spillovers that may be due to information exchanges about job opportunities using the spatial correlation patterns in urban unemployment. There, a model is studied in which agents interact locally with their social contacts. The stationary distribution implied by the model is characterized by positive spatial correlations, and the model parameters are structurally estimated by matching the empirical spatial distribution of unemployment in a metropolitan area with the simulated one generated by the model.

[6] This aspect of the analysis has been largely absent in the existing literature. Notable exceptions include Holzer (1988) and Datcher Loury (2004). The former uses NLSY data to study the choice of search method in a sample of unemployed young males, and finds that informal referrals are the most productive method in terms of job offer and acceptance probabilities. The latter studies the impact of informal referrals on earnings.

[7] Ellison and Glaeser (1997) also consider spatial concentration as a potential indicator of local spillovers: they develop an index of geographic concentration of economic activity that is not sensitive to the specific source of agglomeration, and is easily comparable across industries.

most critical issue is how to distinguish this social interactions hypothesis from other possible factors that may make it more likely for individuals who reside near each other to also work close to one another. For example, agents residing in the same geographic area have very similar access to transportation routes and firm clusters. Further, different socio-demographic groups may be differentially attracted to existing neighborhoods, industrial areas or transportation nodes. Finally, agents who relocated to newly-developed neighborhoods roughly at the same time may have a relatively high propensity to find work in specific firm clusters where employment growth was occurring at that time. The number and scope of potentially unobservable determinants of clustering appears quite daunting, and any analysis that addressed these concerns by simply including observable covariates would leave open the strong possibility that any clustering was driven by unobservables rather than social interactions.

Therefore, we follow an identification strategy that relies on the use of different geographic scales to distinguish these possible effects. First, as a baseline, we compute the probability that two individuals who live in the same Census *block group* work in the same location (a Census block). This probability should incorporate all the observed and unobserved factors that induce undue correlation in the work-residence segments, including the sorting of individuals into locations. We also include a large set of socio-demographic control variables, to capture the influence of geography on specific groups. Then, we compute the likelihood that two individuals living in the same Census *block* work in the same location.[8] To the extent that the latter probability is higher than the former (in a statistically significant sense), we conclude that very local hiring network effects are present.

The identifying assumptions are two-fold: first, we assume that no significant sorting occurs below the level of the block group, due perhaps to the thinness of the housing market. In other words, one may choose her residential location down to the block group level, but the specific block is assigned randomly. Second, we assume that social interactions leading to referrals are very local, and take place within a block. Of course, to the extent that social interactions occur at a larger geographic scale than a block, our estimates represent a lower bound of the importance of network effects in hiring.

After measuring the social interaction effect as the additional propensity for two residents in the same census block to also work together in the same block (both unconditionally and conditioning on the pair's characteristics), we extend the analysis in several directions. First, we examine alternative specifications to address the issue of reverse causation: it is possible that referrals operate in the opposite direction, namely one's co-workers may offer information about potential residential locations to a new hire. We address this possibility by using samples that consider workers who have resided in the current location at least two years, while one of the individuals in

[8] A Census block group is partitioned into several blocks. In our sample, a block group is composed on average of about ten blocks.

the pair was likely to be looking for work last year. Second, we perform a robustness analysis of our estimates with respect to the assumption of no additional sorting at the block level. In particular, we repeat our estimation procedure for several subsamples that empirically exhibit the least amount of sorting with respect to various demographic characteristics.

The final portion of the paper aims at empirically quantifying the importance of the estimated referral effects. We do so by including a measure of match quality (or referral potential) for individual workers into standard regressions for labor force participation, employment, weeks and hours worked, earnings and wages. We define match quality for each individual as the average informational content of that individual's matches with other adults residing in the same Census block. We then study the extent to which a one standard deviation increase in match quality raises the probability of participating in the labor force, expected weeks or hours worked, and so on.

Our estimation results indicate that there are significant social interaction effects at the Census block level. In terms of the magnitude of the effect, the baseline probability of working together at the block group level is about 0.51% on average, but rises to 0.93% going to the block level. Further, our findings are robust to the introduction of detailed controls for socio-demographic characteristics and block group fixed effects, as well as across various specifications intended to address the possibility of local sorting within block groups on the one hand, and reverse causation on the other hand. Finally, our estimated referral effects are found to have a (statistically and economically) significant positive impact on all labor market outcomes under consideration. For instance, a one standard deviation increase in match quality raises expected labor force participation by 1.1 percentage points, weeks worked by about two thirds of one week, and earnings by about two percentage points.

The rest of the paper is organized as follows. Section 2 describes the data set from the Boston metropolitan area. Section 3 contains our estimation methodology both for the basic network effect in hiring, and for the extensions discussed above. We report our empirical results in Sections 4. Finally, Section 5 offers some concluding remarks.

2 Data

A novel and very fruitful aspect of this paper is that we are able to use the restricted access version of the Decennial Census, at the Census Research Data Center in Boston. Essentially, the restricted access version of the Census data contains information on everyone who filled out the long form questionnaire of the Census (about a 1-in-7 sample), and provides information on both residential and employment locations down to the Census block level. For each individual, we observe age, gender and marital status, education, race, family structure, tenure in the residential block. We also observe labor force status, salary and wage income if employed, occupation, industry, and other socio-demographic characteristics.[9] We are focusing on the Boston metropolitan area and have access to the 1990 Decennial Census.

For the baseline network effect analysis, we construct a sample that contains all pairs of currently employed, U.S. born individuals who reside in the same block group within the Boston metropolitan area, who do not belong to the same household, and whose age is between 25 and 59.[10] Overall, the sample contains about 4 million observations on pairs, constructed out of roughly $110,000$ employed individuals. For the labor market outcomes analysis, we use a sample of U.S. born, prime age (25 to 59) individuals who live in the Boston metropolitan area. This sample has roughly $150,000$ observations.

With regard to the geographic structure of the data, there are $2,565$ block groups in our sample, with an average of 10 blocks each. The distribution of blocks per block group ranges from one to 54, and is depicted in Figure 1: the median number of blocks per block group is roughly eight, and about 95% of all block groups have 20 blocks or less. The average number of workers per block is 4.7 (47 workers per block group). Figure 2 reports the corresponding histogram: the median number of workers per block is about three, and 95% of all blocks contain 13 workers or less. The Census block definition refers to the physical area (typically roughly rectangular) delimited by four streets intersecting each other. As such, it excludes buildings that face each other on the same street. Therefore, to the extent that social interactions occur between residents on opposite sides of the same street, our estimated network effect is a lower bound of the "true" effect.[11]

3 Estimation Strategy

In this Section, we study the empirical question of detecting informal network effects in job search by analyzing the baseline model for whether pairs of employed individuals living in the same residential location also work in the same location. The maintained hypothesis, simply put, is that agents interact very locally with their social contacts, exchanging information about jobs. In particular, when unemployed, an individual may receive referrals from her employed contacts about job opportunities offered by their employers (or available at nearby firms in the same work location).

[9] In future work, we plan to use detailed information on language spoken at home, ancestry, and immigration/citizenship status to focus more precisely on several dimensions along which social networks are constructed.

[10] "Currently employed" refers to the reference week in calendar year 1990 used by the Census. Also, notice that the matching algorithm drops all matches where the second individual's household identification number is less than or equal to the first individual's number in order to eliminate duplicate pairs.

[11] Depending on the specific neighborhood, one may argue in the opposite direction: streets may effectively act as dividers of local communities, and interactions may be strongest in the alleys and courtyards connecting the rear sides of buildings on the same block. This is consistent with our assumption of 'within-block' interactions.

This pattern of information transmission generates a linkage between the residential location of a pair of socially connected individuals and their work locations, inducing clustering in the work-residence segments in our sample. Other things being equal, such clustering would not arise if agents simply searched for jobs at a cost that is increasing in the distance from their residential location.

3.1 Baseline Specification

The empirical strategy used in our baseline analysis is quite intuitive. As we mentioned in Section 1, our objective is to examine the difference in the propensities to work at the same location (block) for pairs of individuals who reside in the same block group and in the same block, respectively. Under the assumption that social interactions are very local and that no significant sorting occurs below the level of the block group, a test for the statistical significance of the difference between these propensities would be a test for social interactions in employment locations.

Formally, our baseline specification is the following linear probability model:

$$W_{ij}^b = \rho_g + \beta' X_{ij} + (\alpha_0 + \alpha_1' X_{ij}) \cdot R_{ij}^b + \varepsilon_{ij}, \tag{1}$$

where i and j denote two individuals who reside in the same Census block group but not in the same household, W_{ij}^b is a dummy variable that is equal to one if i and j work in the same Census block, R_{ij}^b is a dummy variable that is equal to one if i and j reside in the same Census block, X_{ij} is a vector of socio-demographic control variables for the matched pair (i, j), and ρ_g denotes the residential block group fixed effect – this is our baseline probability of working in the same block for individuals residing in the same block group. Our test for the presence of social interaction effects then is simply a test of the statistical significance of the estimated $\left(\widehat{\alpha}_0 + \widehat{\alpha}_1' X_{ij}\right)$.[12]

The estimated coefficients on the cross terms, $\widehat{\alpha}_1'$, allow us to investigate whether the social interaction effect is weaker or stronger for specific socio-demographic characteristics of the matched pair. There are two aspects to this: first, certain pairs are more likely to interact because of the assortative matching present in social networks: for instance, two individuals of similar age, education, race, or with children of similar age.[13] Second, certain individuals may be more strongly attached to the labor market and may thus provide better referrals or information on jobs – for example, college graduates, married males or individuals with children. In this case, matches between pairs in which one individual is strongly attached to the labor market and the other generally more likely to need a referral should also lead to an increased social interaction effect.

[12] As a preliminary, in Section 4 we also report estimates for a version of (1) without covariates: $W_{ij}^b = \rho_g + \alpha_0 R_{ij}^b + u_{ij}$. In this case, testing for the presence of social interactions amounts to testing the null hypothesis that $\alpha_0 = 0$.

[13] See Marsden (1987), (1988) for a discussion of the evidence from the General Social Survey on assortative matching in networks.

By including the baseline probability of an employment match for individuals living in the same block group, $\widehat{\rho}_g$, as well as the pair's covariates in levels, $\widehat{\beta}' X_{ij}$, we are able to control for any observed and unobserved factors that may influence the employment locational choices at the block group level. For example, as we mentioned in the Introduction, features of the urban transportation network (both observed and unobserved) might induce clustering in the segments that connect work and residential locations. In other words, people who live physically near each other may have very similar access to transportation networks and/or employment clusters.

Further, worker characteristics (again, both observed – such as race/ethnicity, education, occupation – and unobserved – religion, cultural traits, etc.) might be correlated *both* with their residential locational preferences *and* with the likelihood to work in a given location, if firm locations tend to cluster along these same attributes. For instance, members of certain demographic groups may be more likely to live together on the one hand, and choose jobs near central transportation nodes or in specific industrial clusters: as a result, these groups will be more likely to work in the same location. This potential problem is directly addressed by the inclusion of demographic controls in levels, $\widehat{\beta}' X_{ij}$. These controls absorb out the general propensity of certain types of individuals who live in the same block group to work together, allowing the comparable parameters for individuals who reside on the same block, $\widehat{\alpha}_1'$, to identify the strength of the social interaction for these individuals.

Temporal issues might also complicate the analysis. Suppose current residents of a given block group all moved in at similar times because the neighborhood was developed at that time. Since employment and residential changes often move together (temporally), it is possible that many residents of that neighborhood may have found jobs in similar locations, i.e. where employment growth was occurring at the time. This source of bias is addressed in the same way as the ones above: in this case, the inclusion of level controls for age and tenure in residence are especially noteworthy because one provides information on when the individual most likely entered the labor market and the other contains controls for when the individual moved to this particular neighborhood.

An additional source of bias may derive from the fact that block groups are designed to fall within a given population range while blocks are physical blocks, so that some block groups contain only a handful of very densely populated blocks whereas others have up to a few dozens low-density blocks. This construction of block groups creates a correlation between the variable that records whether two matched individuals reside in the same block, R_{ij}^b, and the population density within the block group. Density, however, is also likely correlated with access to transportation systems and employment clusters, and may therefore affect the likelihood that two individuals work together: hence a potential bias. Again, we are able to avoid this bias by including block group fixed effects that capture the across block group differences in the effect of geography on the likelihood that two individuals work together.[14] We also add a specific control for the population of the particular blocks in which each member of a given pair resides within the block group, to pick up any local density effect.

In this way, our empirical strategy aims at isolating the network referral effect from these other confounding factors, without having to specify a full-blown behavioral model of residential and employment location decisions. The advantages of this are two-fold. On the one hand, we do not have to worry about the possibility of correlated unobservables generating the observed locational patterns. On the other hand, our strategy is not sensitive to possible misspecification of such a choice model.

The downside to such a strategy is that it relies crucially on the premise that social interactions are likely to occur at the block level, while households are only able to choose a block group at the time of the location decision, due perhaps to the thinness of the housing market. The first part of the premise does not seem too far-fetched, given that we only require that at least *some (not all)* social interactions be very local, and that this is supported by existing sociological and ethnographic evidence. The second part of the premise may be more problematic, insofar as households do sort down to the block level.

We address this problem by first examining block homogeneity within block groups. We ask whether blocks are substantially more homogeneous that block groups, where our standard of comparison is based on how much more homogeneous block groups are, relative to census tracts. Then, we use this information to draw a subsample of block groups in which blocks exhibit the least amount of sorting, and re-estimate the baseline model for the restricted sample in order to see if our results are robust across samples.

An additional way to determine whether sorting at the block level is indeed a concern is to compare the coefficient estimates for the matched pair's covariates X_{ij}, in levels and as interactions with the block dummy R^b_{ij} (i.e., $\widehat{\beta}'$ and $\widehat{\alpha}'$ respectively). Assuming that the results at the block group level, which are captured by the level coefficients, are driven primarily by the types of factors that would bias our analysis, then $\widehat{\beta}'$ describe the empirical correlations that arise from these biases. If the biases at the block group level are similar to those at the block level and only the geographic scale has changed, then one would expect to see a qualitatively similar result at the block level (namely, in $\widehat{\alpha}'$). This does not seem to be the case in our empirical analysis.[15]

[14]Note that the structure of the analysis is based on a sample of pairs living in the same block group, so that block group fixed effects are not needed as a way of ensuring that the model is identified using only within-block group variation. Instead, as the discussion in this paragraph makes clear, the inclusion of block group fixed effects allows for heterogeneity across the metropolitan area in the baseline propensity of individuals residing in the same block group to work together.

[15]The limitation of this argument should also be clear. When there are several biases that work in different directions, the relative magnitudes of the biases may change as we shift the level of

A separate confounding issue is the possibility that the estimated social interaction effect may be due to reverse causation: workers could receive tips and referrals about residential locations from their co-workers at a given firm. We address this issue in several ways. First, the empirical focus on the difference between block group and block level propensities again mitigates this problem because residential referrals are unlikely to result in people residing in exactly the same block, due to the thinness of the housing market at the block level. Further, we tackle the reverse causation problem directly by estimating (1) on a subsample where both respondents in a given matched pair have lived in that neighborhood for at least two years, but one of them was not fully employed last year. Unfortunately the Census does not contain any direct information on job search activity. Therefore, we use the "not fully employed last year" category as a proxy for the set of individuals who are most likely to have been actively searching for a job last year.[16] We also estimate an intermediate specification using the subsample of pairs whose members were both in residence at least two years, and adding controls for whether one and/or both individuals were fully employed last year.

Finally, one word about inference. The sampling scheme, which is based on drawing matched pairs of individuals who reside in the same block group, makes it very difficult to compute appropriate standard errors for our estimates. In particular, the observations in our sample – pairs of individuals in the same block group – do not constitute a random sample. In fact, suppose that individuals a and b work in the same block. Suppose further that individuals b and c work in the same block. Then, by transitivity, individuals a and c also work in the same block. As a consequence, if we compute standard errors via the basic OLS formula, we may tend to understate their size because we are not taking into account this inherent correlation structure in our data. In practice, however, the OLS standard errors represent a very good approximation: since only a very small percentage of pairs actually work in the same block the overall sample is close to an independently distributed sample. Therefore, we report OLS standard errors in our Tables.[17]

geography and as a result the sign of the bias might reverse. For example, at the block group level, most of the results may be driven by individual observable heterogeneity, but at the block level residential sorting on unobservable might become more important.

[16] Formally, "not fully employed last year" refers to individuals who worked less than 40 weeks *or* less than 30 hours per week last year (i.e., in calendar year 1989).

[17] We have compared the OLS standard errors to those obtained via the following bootstrap procedure. We independently draw 400 1-in-20 subsamples with replacement from the original sample of pairs. We then compute estimates $\left(\widehat{\alpha}_0, \widehat{\alpha}_1, \widehat{\rho}_g, \widehat{\beta}\right)$ for each subsample, and plot their empirical distribution. The standard errors are calculated from the variance of this empirical distribution. The bootstrapped standard errors are very similar to the OLS ones.

3.2 Labor Market Outcomes

Having estimated the extent of the social interaction effect in our baseline specification, we then turn to investigating the impact of this network effect on various labor market outcomes. Since the strength of the social interactions effect may vary with the type of matches – as indicated by the analysis in the baseline specification – we wish to see whether in fact the quality of matches available in an individual's block affects employment, labor force participation, and wage outcomes.

We have two objectives here. First, since we are attempting to detect informal hiring effects indirectly, we want to study the connection between our estimated effects and labor outcomes more closely, in order to enhance the plausibility of our social interactions results. Second, by focusing on outcomes we hope to be able to provide a better sense of the magnitude of our estimated network effects. As we noted in the Introduction, most of the existing literature on informal search methods does not analyze their impact on aggregate labor market outcomes.

For this analysis, the unit of observation is an individual rather than a pair. For the employment and labor force participation outcomes, the econometric model is a linear probability model.[18] The likelihood of falling into one of these discrete categories is specified as a linear function of household, individual, and neighborhood variables. For all other outcomes, such as weeks worked, hours-per-week worked, wages and earnings (in logs), we use a simple linear regression.

We then add – for each model specification – a 'network quality' proxy variable for each individual, which is constructed by examining that individual's matches with other adults in her block, using the coefficient estimates $\widehat{\alpha}_1$ from the estimation of (1). Specifically, the match quality variable for individual i, Q_i, is constructed using a sample of all possible pairings of individual i with other individuals who reside in the same block and do not belong to the same household. For each pair, a linear combination M_{ij} of the pair's covariates is created using the estimated parameters from the interaction of these variables with R^b_{ij} in (1): $M_{ij} = \widehat{\alpha}_1' X_{ij}$. Then, Q_i is computed as the mean value of M_{ij} over all matches for individual i:

$$Q_i = \frac{1}{|N_i|} \sum_{j \in N_i} M_{ij}$$

where N_i is defined as the set of social contacts of agent i: $N_i = \left\{ j : R^b_{ij} = 1 \right\}$.

We would expect individuals with good matches in their block – high value of Q_i – to have better labor force outcomes on average, after controlling for the direct effect of their attributes, the average attributes of their block, and block group fixed effects. We repeat the analysis for each of the various specifications described in Section 3.1 to address the sorting and reverse causation issues. In particular, by using a subsample

[18] We have also performed our analysis using a multinomial logit specification, with three discrete outcomes: out of the labor force, unemployed, and employed. The results are qualitatively very similar.

of individuals that were not fully employed last year, we focus on the group that was most likely to have been looking for work in the past year. We expect the effect of Q_i on labor market outcomes to be more strongly positive if the individual was working less than full time in the previous year, because we would be more likely to detect an actual instance of using one's referral network during an active job search.

The actual specification used is

$$E_i = \theta_g + \delta_1' X_i + \delta_2' \overline{X}_i + \delta_3' Q_i + u_i, \tag{2}$$

where θ_g are standard block group fixed effects, X_i is the vector of individual attributes that are the same set of attributes used in the workplace clustering specification, and $\overline{X}_i$ is the vector of block averages on the same attributes. The latter are included in order to control for overall or non-individual specific effects of neighborhood on employment.

In principle, this model is identified with block fixed effects because Q_i varies across individuals in a block. In our opinion, however, it would not be appropriate to include block fixed effects in this model. The current specification with block group fixed effects is identified because similar individuals reside in different blocks within the same block group and therefore have different match quality. In other words, the conceptual experiment considered is to change the match quality for a generic individual with observables X_i by moving them from one block to another block in the same block group, which we believe is the appropriate comparison or exercise. A specification that included block fixed effects would be identified by a comparison of individuals with different match quality in the same block, but individuals with the same X_i have exactly the same Q_i if they are in the same block. Therefore, the associated, and in our opinion undesirable, conceptual experiment would involve changes in an individual's observable attributes and conditioning out of the direct effect of that change in observable attributes in order to measure the effect of a change in their match quality. Clearly, the results of the second exercise are likely to be very sensitive to parametric assumptions concerning how X_i enters labor market outcomes and are unlikely to provide reliable insights into the magnitude of our social interaction effects.

Finally, it is important to point out a limitation of this exercise. In particular, what is actually identified by the first-stage analysis are types of pairs that are more likely to work together due to the strength of the referral effect between the pair. As discussed above, we expect this effect to be large in two cases: (i) when a pair is more likely to interact within their residential neighborhood and (ii) when one person is well attached to the labor market and the other likely to need a referral. In this way, for a person that is not well attached to the labor market, the measure of match quality described here should do a good job of characterizing the quality of matches in a neighborhood. For a person better attached to the labor market, however, our match quality variable may actually measure neighborhoods in which such a person provides rather than receives referrals. In this way, to the extent that our estimated social interaction effects in the first stage of our analysis are driven by the asymmetry in labor market attachment rather than by the strength of neighborhood interactions, our analysis of the effect of match quality on labor market outcomes is likely to understate the benefits of improved matches.

4 Empirical Results

In this Section we first present some summary statistics for our data. We then report the estimation results for our baseline specification and for its various extensions. Finally, we discuss the labor market outcome regressions.

Table 1 contains summary statistics for our matched pairs sample. The second column contains the mnemonic code for the category. The third column reports the relative frequency of each type of pairs in the sample: less than ten percent of all pairs involves at least one high school dropout; most pairs (94%) are all White; roughly three quarters have at least one member with children; only about 15% involve individuals that are single. The fourth column reports – for each category – the empirical frequency of working in the same block: by construction, this represents an estimate of the probability of working together for pairs whose members live in the same block group. It should be noted that the sample contains only a small fraction of native born Asians and Hispanics and so these two groups are combined.[19] The last column reports the same empirical frequency given that both individuals also live in the same block. The first row then indicates that the baseline probability of working together at the block group level is about 0.51% on average, but rises to 0.93% going to the block level.[20] Almost all groups see an increase in the probability of working together when we move from the block group to the block. The increases are especially large, however, for pairs where both are college graduates, both have children, one individual is white and one is black, both are young, and both are married females.

Table 2 reports summary statistics for our sample of individuals. As with Table 1, the second column contains a mnemonic code, and the third column contains the category frequencies. The last four columns contain labor market and commuting information. College graduates, married males and individuals with children display the strongest attachment to the labor force, with respect to both employment rates and weeks worked. These groups also tend to work the farthest away from home, considering both commuting time and physical distance. One the other hand, high school dropouts and married females tend to have weak labor force attachment and work close to home under both commuting metrics.[21]

[19] Estimations where these groups are separated yield very similar results.

[20] The average probability of working together for two individuals who reside in the same block group but not in the same block is 0.44%.

[21] Interestingly, Blacks seem to have the shortest commute with respect to physical distance, but the longest in terms of time. This may reflect a higher usage of public transportation for this group.

4.1 Baseline

The first two columns of Table 3 contain the estimation results for the baseline specification in (1), using our full sample. The first row reports the parameter estimate for α_0 in the case with block group fixed effects but without covariates X_{ij}: this is positive and very statistically significant, indicating a strong additional propensity for two workers living in the same block to also work in the same block, over and above the estimated propensity for matches in their block group.

Turning now to the full specification with covariates, the remaining rows are assembled by groups of variables, such as educational attainment or race/ethnicity of workers in the pair, where the parameter estimates for the level coefficients are listed for the entire set of variables followed by the parameter estimates for the variables when interacted with whether the two workers live on the same block, bmatch. The estimated social interaction effect is represented by $\left(\widehat{\alpha}_0 + \widehat{\alpha}_1' X_{ij}\right)$ in equation (1) and captured by the parameter estimates for the interaction variables. These estimates are positive and statistically significant for most of the socio-demographic categories in X_{ij}.[22] The interaction effects vary by group in interesting ways. With respect to education, stronger interactions occur for matches where both individuals are high school graduates or (less so) college graduates. This is consistent with two common empirical findings in the existing literature on social networks and on informal hiring channels: first, that there is strong assortative matching within social networks and, second, that informal referrals are more prevalent for relatively less educated workers.[23] The results on race and ethnicity are statistically insignificant due to the small number of native born minorities in the Boston metropolitan area, but the magnitude of the effect of a match between blacks is similar to the effect found for a match between high school graduates.

We also find significant referral effects for matches between households with children, and especially where both households have pre-school age or teenage children, and between workers of similar ages. Again, these results seem highly consistent with the existing empirical consensus on positive sorting in social networks.[24] Further, we find very strong interaction effects for all gender and marital status categories relative to matches between married females. Matches where at least one of the members is a married male are especially strong, which is consistent with the notion that married males have a particularly strong attachment to the labor force and therefore may be better sources of referrals. Finally, social interactions are slightly stronger for smaller

[22] The negative intercept $\widehat{\alpha}_0$ in the case with covariates means that the effect is negative (but barely statistically significant) for the left out category: this is for matches between Asians and Blacks, where one person is a high-school graduate and the other is a college graduate, and one person is 25 years old while the other is 35, etc. Such a category is a very tiny portion of all pairs in the sample.

[23] See, for example, Corcoran et al. (1980).

[24] Also, older workers tend to experience larger referral effects: this is consistent with the empirical evidence reported in Granovetter (1995).

blocks: this is encouraging since such areas typically have fewer housing units and represent thinner housing markets – hence with less scope for sorting within block groups.[25]

Finally, there seem to be striking differences between the level and the interaction coefficients associated with the X_{ij} covariates. For example, pairs of married females are the most likely to work in the same block (perhaps because they tend to work close to home), but also have the weakest referral effects among all gender and marital status categories, which is consistent with their relatively low labor force attachment. Similarly, high school dropouts are more likely to work together, but do not exhibit stronger referral effects than other education categories. These differences between the estimated $\widehat{\alpha}$ and $\widehat{\beta}$ coefficients are reassuring in light of our discussion with regard to sorting in Section 3.1.

The second block of columns in Table 3 reports estimation results for the subsample of matches between individuals who have lived in that block group for at least two years and includes controls for whether either of the workers were not fully employed last year. The results are qualitatively similar to those in the baseline regression with the exception of the gender/marital status and the race/ethnicity categories. For this sample, the married female effect is not robust possibly because the controls for full employment last year successfully capture the labor force attachment differences between married women and other workers. In terms of racial/ethnic groupings, the interactions are particularly strong for matches in which at least one member is white where the omitted category is a match between individuals belonging to the Hispanic or Asian group. Again, this is consistent with a referral interpretation, since whites tend to be in the labor force more consistently than other groups and can therefore be expected to provide referrals on a more regular basis.

The key result in this specification, however, is that social interactions are stronger for matches in which one of the individuals was not fully employed the previous year while the other individual was, whereas interaction effects are dramatically weakened when both members of the pair were not fully employed the previous year. This is entirely consistent with our job referral hypothesis, as one would expect referral effects to be the most prominent for the former type of matches, and the least important for the latter. In addition, since these are workers who have resided in the same location for at least two years, these findings do not lend support to the reverse causation hypothesis (co-workers giving referrals about desirable residential locations to new employees).

The last set of columns in Table 3 focuses on the subsample of pairs with both individuals in residence at least two years, but with only one member fully employed in the previous year. Again, this sampling scheme reduces the possibility of reverse causation, since we are considering workers who are more likely to have made a transition to full employment during the past year *and* whose residential tenure is

[25] Alternatively, one could think that social interactions are weaker in larger blocks because it is more difficult to establish and maintain a social contact in such a block.

longer than two years. At the same time, by looking at pairs in which one was fully employed while the other was not, we are focusing on instances in which it is most likely that a referral or information exchange actually took place.

As in the other specifications, the estimated social interaction effect is strongly positive and statistically significant for the version without covariates: if anything, the size of the estimated $\widehat{\alpha}_0$ is about 50% larger than using the full sample (0.0039 vs. 0.0024). When we introduce covariates, the estimation results become statistically weaker than in the larger samples, due in part to the smaller sample size. Qualitatively, however, our previous results are confirmed, especially with respect to the fertility and age characteristics of the match. Overall, these findings strongly support the job referral hypothesis and make the reverse causation argument unlikely.

4.2 Sorting within Block Groups

Our identification strategy relies on the assumption that while households are able to choose their residential locations, they cannot choose the specific block of residence. In other words, there may be sorting across block groups, but not much additional sorting within them. Here we wish to investigate this issue empirically, by studying the extent of assortative matching along various observable socio-demographic attributes.

In particular, for a specific characteristic (e.g., education), we calculate the average exposure rate of a high school dropout to all education sub-categories, at three different levels of geography: the census tract, the block group, and the block. The goal is to see whether there is significant additional sorting going from the block group to the single block, relative to the sorting that occurs going from the census tract to the block group.

This analysis is reported in Table 4. The main result is that there seems to be some (but not strikingly so) additional sorting on the basis of education, race, and age. For example, on average a Black individual lives in a tract that is 43% Black; this percentage rises to 46% at the block group level, and rises further to 53% at the block level.[26] On the other hand, there is clearly strong additional sorting at the block level with respect to the presence and age of children. This is perhaps due to the locational choices induced by a desired proximity to schools.

Since we do observe some additional sorting at the block level, we then re-estimate our baseline specification using a subsample of matches drawn from blocks where the least amount of additional sorting takes place (i.e., blocks below the median amount of additional sorting with respect to a specific attribute). The results of this estimation, for different samples based on education, race, and presence of children, are collected in Table 5.

[26] Note that there are many more blocks in the average block group than block groups in the average tract.

The main findings of our baseline specification (Table 3, columns 1-2) are confirmed and, in some cases, strengthened. Most socio-demographic categories experience positive and statistically significant referral effects. The results for age, presence of children, and gender/marital status are very similar qualitatively to our baseline. The education results confirm that the education categories involving matches between individuals with the same educational attainment (especially for High School graduates) are characterized by stronger social interactions. The presence of children especially of pre-school or high school age lead to stronger social interactions, and for age strong benefits from social interactions primarily arise between individuals who are both similar in age (thus likely to interact) and older (thus likely to provide referrals). Finally, the effects for race are strengthened sufficiently to rise to the level of statistical significance. Specifically, after controlling for sorting attributable to race or educational attainment, pairs containing two blacks or at least one white worker exhibit considerably larger positive effects of social interactions than the omitted category that includes matches between workers in the Hispanic or Asian group.

In sum, it seems that our estimated social interaction effects persist, even in areas that do not experience a significant degree of sorting below the block group level – at least along observable characteristics. We believe that this set of results further validates our attempt to isolate referral effects from sorting via the identification strategy proposed in this paper.

4.3 Labor Market Outcome Regressions

In this Section, we wish to look more closely at the economic significance of the referral effects reported above by examining the impact of match quality on various labor force outcomes. In particular, we perform a set of standard labor force participation, employment and wage regressions that include a full set of controls for individual characteristics, average characteristics of the corresponding Census block, and block group fixed effects. These regressions are augmented to include a match quality variable Q_i constructed using the estimated social interaction effects from the various specifications in Section 4.1.

Table 6, columns 1-3 collects our estimation results for the case in which the full sample of individuals is used, and Q_i is constructed with the estimated $\widehat{\alpha}_1$ from (1) using the full sample of pairs (Table 3, columns 1-2). For each dependent variable, we only report the coefficient estimates associated with match quality for the sake of expositional clarity.[27,28] The main result is that our match quality proxy has a positive and very significant impact on all dependent variables under consideration except employment conditional on labor force participation. For example, a one stan-

[27] The estimation results for the full sets of individual and block-level covariates are quite standard and are available from the authors upon request.

[28] The first three dependent variables refer to labor market outcomes for the week preceding the census survey. The last four variables represent labor market outcomes for the preceding year.

dard deviation increase in match quality raises labor force participation by about 1.1 percentage points, weeks worked by two thirds of a week, earnings by two percentage points and wages by 1.4 percentage points. Therefore, our estimated referral effects do seem to be associated with improved labor market outcomes especially as it concerns participation in the labor market and the intensity of that participation.[29]

Columns 4-6 in Table 6 report estimates for the same set of regressions performed on the subsample of individuals who were in residence in their current block for at least two years (again using the $\widehat{\alpha}_1$ estimates from the corresponding regression in Table 3, columns 3-4). The same pattern of results holds here, although the magnitude of the effects is onr third to one half weaker than for the full sample. Interestingly, the estimated coefficient for Q_i in the wage regression becomes statistically insignificant in this specification.[30]

We take a more detailed look at the effect of match quality on labor market outcomes in Table 7. The objective here is to focus on individuals who were more likely to be searching for a job and thus more likely to receive, rather than provide, referrals. In columns 1-5, we report estimates for the same set of regressions performed in the second panel of Table 6 (using the subsample of individuals that were both in residence at least two years), but adding a dummy variable for whether the individual was not fully employed last year. We then report the coefficient estimates both for our measure of match quality and for the interaction term of match quality with the 'not-fully-employed' dummy. The results are quite striking: match quality per se does not have a significant impact on any outcome for the individuals who were fully employed last year, whereas it has strongly positive and significant effects for the individuals who were not fully employed, and thus more likely to benefit from referrals. The economic magnitude of the effect is larger than in the full sample case for labor force participation (1.3 rather than 1.1 percentage points), and is very large (2.4 percentage points) for employment conditional on labor force participation.

The second set of results in Table 7 (columns 6-8) takes a slightly different approach by focusing on the subsample of workers who were in residence for at least two years and, further, who were not fully employed last year (using the estimated $\widehat{\alpha}_1$ coefficients from the corresponding regression in Table 3, columns 5-6). Again, we would expect match quality to be especially important for this subset of workers. We find that match quality has a slightly larger effect on labor force participation than in the full sample case. However, the statistical significance of this result is weakened

[29]Recall from our discussion above that this analysis will tend to understate the benefits of improved match quality at the block level as the quality of local matches will typically be overstated for individuals who generally provide referrals. Also, note that since Q_i contains measurement error, there is likely to be some attenuation bias in our estimates.

[30]The empirical literature on informal hiring channels contains mixed evidence on the earnings effect of job networks. Datcher Loury (2004) reports that, in aggregate, informal channels do not seem to lead to higher earnings than formal ones: however, specific types of referrals (e.g., from older male relatives) do generate significantly higher earnings. Marmaros and Sacerdote (2002) also report a positive association between earnings and informal contacts.

because of the reduced sample size.[31]

Finally, Table 8 reports the impact of match quality on the same set of labor market outcomes as in Table 6, for the subsamples of matches drawn from blocks in which the least amount of sorting takes place. Again, for each specification the estimated $\widehat{\alpha}_1$ are used from the corresponding regressions reported in Table 5. The results are qualitatively and quantitatively similar to the ones obtained using the full sample, confirming the robustness of our analysis to the potential issues induced by sorting.

5 Conclusions

This paper aims at detecting the presence of informal referral effects in the labor market by using a novel data set and identification strategy. We find significant evidence of social interaction effects at the block level. The baseline probability of working together at the block group level is about 0.51% on average, but rises to 0.93% going to the block level. These findings are robust to the introduction of detailed controls for socio-demographic characteristics and block group fixed effects, as well as across various specifications intended to address biases caused by sorting below the block level and housing market referrals exchanged between people who work together. Furthermore, the relationship between socio-demographic characteristics and the strength of social interactions make sense. Social interactions tend to be stronger when the match involves individuals who are likely to interact because they are similar in terms of education, age, and presence of children. Interactions also appear to be stronger when they involve at least one type of individual who is strongly attached to the labor market leading to weaker interactions when both members of the pair are high school drop-outs, young, or married females.

Furthermore, our estimated referral effects have a positive impact on labor market outcomes. Even after controlling for individual attributes, observable block attributes, and unobservable block group attributes using fixed effects, an individual's match quality is a statistically significant determinant of most labor market outcomes considered across all of our specifications. In terms of economic magnitude, a one standard deviation increase in referral opportunities raises expected labor force participation by one percentage point, weeks worked by about two thirds of one week, and earnings by about two percentage points.

This paper provides a new approach for examining the effect of social interactions based on variation in geographic scale, and this approach might be useful in a variety of contexts. For example, in the case of welfare participation, the block of residence is unlikely to greatly influence access to public service providers after controlling for the block group, and in the case of intellectual spillovers it seems unlikely that a firm's access to local suppliers or the regional labor market (the other two major sources of

[31] The p-value is roughly 0.12 for a two-sided test of the null hypothesis that the parameter is zero.

agglomeration economies) would vary much within individual block groups. In future work on social interactions on employment, we plan to extend this analysis to two groups of individuals for whom we expect informal hiring networks to be especially important: namely, young adults and recent immigrants.

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6 Appendix

The following are the definitions of the variables used in the empirical exercise.

bmatch: dummy variable equal to one if both members of the pair reside in the same Census block, zero otherwise.

Education

hsd_hsd: dummy variable equal to one if both members of the pair are high school dropouts, zero otherwise.

hsg_hsg: dummy variable equal to one if both members of the pair are high school graduates, zero otherwise.

clg_clg: dummy variable equal to one if both members of the pair are college graduates, zero otherwise.

Race

wht_wht: dummy variable equal to one if both members of the pair are White, zero otherwise.

bl_bl: dummy variable equal to one if both members of the pair are Black, zero otherwise.

bl_wht: dummy variable equal to one if one member of the pair is Black and the other is White, zero otherwise.

ashi_wht: dummy variable equal to one if one member of the pair is Asian or Hispanic and the other is White, zero otherwise.

Fertility

child_m: dummy variable equal to one if both members of the pair have children, zero otherwise.

c05_05: dummy variable equal to one if both members of the pair have children between 0 and 5 years of age, zero otherwise.

c612_612: dummy variable equal to one if both members of the pair have children between 6 and 12 years of age, zero otherwise.

c1317_1317: dummy variable equal to one if both members of the pair have children between 13 and 17 years of age, zero otherwise.

c1824_1824: dummy variable equal to one if both members of the pair have children between 18 and 24 years of age, zero otherwise.

Age

a25_25: dummy variable equal to one if both members of the pair are between 25 and 34 years of age, zero otherwise.

a35_35: dummy variable equal to one if both members of the pair are between 35 and 44 years of age, zero otherwise.

a45_45: dummy variable equal to one if both members of the pair are between 45 and 59 years of age, zero otherwise.

a35_45: dummy variable equal to one if one member of the pair is $35 - 44$ and the other is $45 - 59$ years of age, zero otherwise.

Gender and Marital Status

sm_sm: dummy variable equal to one if both members of the pair are single males, zero otherwise.

sf_sf: dummy variable equal to one if both members of the pair are single females, zero otherwise.

sm_sf: dummy variable equal to one if one member of the pair is a single male and the other is a single female, zero otherwise.

mm_mm: dummy variable equal to one if both members of the pair are married males, zero otherwise.

mm_mf: dummy variable equal to one if one member of the pair is a married male and the other is a married female, zero otherwise.

sm_mf: dummy variable equal to one if one member of the pair is a single male and the other is a married female, zero otherwise.

sm_mm: dummy variable equal to one if one member of the pair is a single male and the other is a married male, zero otherwise.

sf_mf: dummy variable equal to one if one member of the pair is a single female and the other is a married female, zero otherwise.

sf_mm: dummy variable equal to one if one member of the pair is a single female and the other is a married male, zero otherwise.

Tenure in Residence, and Size of Census Block

lngth: the sum of the household times in residence for the two members of the pair.

lngth_min: the minimum of the household times in residence for the two members of the pair.

lngth_within 5: dummy variable equal to one if the household times in residence for the two members of the pair are within five years of each other, zero otherwise.

blocksize: the total population of the Census blocks in which the two members of the pair reside.

TABLE 1

Matched Pairs Sample: Summary Statistics

Variable Name	Code	percentage	work together	live/ work together
full sample			0.51	0.93
Both high school drop out	hsd_hsd	0.38	0.75	0.94
Both high school graduate	hsg_hsg	18.63	0.69	1.41
Both college graduate	clg_clg	32.36	0.4	0.74
HS drop out - HS grad	hsd_hsg	4.68	0.73	1.05
HS drop out – College grad	hsd_clg	4.25	0.52	0.77
HS grad – College grad	hsg_clg	39.7	0.48	0.89
Both White	wht_wht	94.03	0.5	0.86
Both Black	bl_bl	0.55	0.63	1.3
White – Black	bl_wht	2.81	0.67	2.09
White – Asian/Hispanic	ashi_wht	2.38	0.56	1.33
Black – Asian/Hispanic	ashi_bl	?	?	?
Both have children	child_m	28.8	0.65	1.58
Both have children age 0-5	c05_05	3.55	0.68	2.64
Both have children age 6-12	c612_612	4.53	0.83	2.28
Both have children age 13-17	c1317_1317	3	0.79	1.76
Both have children age 18-24	c1824_1824	3.28	0.65	0.87
No children	nokid_m	25.74	0.41	0.59
Both age 25-34	a25_25	14.22	0.53	1.25
Both age 35-44	a35_35	11.34	0.51	1.01
Both age 45-59	a45_45	9.36	0.56	0.87
Age 25-34 and age 45-59	a25_45	20.14	0.47	0.71
Age 35-44 and age 45-59	a35_45	19.95	0.52	0.86
Age 25-34 and age 35-44	a25_35	23.44	0.48	0.93
Both single male	sm_sm	3.22	0.39	0.54
Both single female	sf_sf	4.3	0.46	0.66
Single male–single female	sm_sf	7.21	0.4	0.49
Both married male	mm_mm	13.69	0.44	1.09
Married male–married female	mm_mf	21.99	0.53	1.37
Single male-married female	sm_mf	8.52	0.53	0.68
Single male-married male	sm_mm	10.37	0.41	0.61
Single female-married female	sf_mf	9.84	0.55	0.8
Single female-married male	sf_mm	11.97	0.38	0.55
Both married female	mf_mf	8.9	0.89	2.06

TABLE 2
Individual Sample: Summary Statistics

Variable Name	Code	percentage	% employed	weeks worked	Commute Time	Commute Distance
full sample			81.73	47.6	23.9	6.9
high school drop out	hsd_p	7.63	60.41	45.4	21.8	5.3
high school graduate	hsg_p	42.98	78.51	47.3	22.2	6.5
college graduate	clg_p	49.39	87.82	48	25.4	7.5
age 25-34	a25_34_p	37.91	82.2	47.2	24.8	7
age 35-44	a35_44_p	31.82	83.14	47.6	23.8	7.1
age 45-59	a45_59_p	30.27	79.63	48	22.8	6.7
single male	sm_p	17.69	82.91	47.3	24	6.4
single female	sf_p	20.53	81.99	47.6	24.5	5.9
married male	mm_p	30.22	92.13	50	26.4	8.8
married female	mf_p	31.56	70.93	45.3	20.3	6
have children	c0_0_p	48.97	84.43	48	24.7	6.7
have children age 0-5	c0_5_p	19.25	74.64	46.9	25.4	8.1
have children age 6-12	c6_12_p	19.89	77.27	46.5	22.6	7.3
have children age 13-17	c13_17_p	15.09	82.08	46.9	22.1	6.9
have children age 18-24	c18_24_p	16.76	81.44	47.8	22.3	6.7
White	white_p	93.86	82.47	47.7	23.8	7
Black	black_p	3.98	72.3	46	27	5.2
Asian/Hispanic	ashi_p	2.15	66.67	45.3	24	5.3
lived in block for < 2 years	live0	15.03	82.16			
lived in block for >= 2 years	live2	84.97	81.65			
not fully employed	nfulle	24.63	38.59	21.5	20.5	5.5
fully employed	fulle	75.37		50.9	24.3	7.1

Summary statistics based on individual sample: obs: 151572
for employed, average variables, obs: 110444

TABLE 3

		BASELINE SPECIFICATION FULL SAMPLE		BOTH IN RESIDENCE AT LEAST TWO YEARS		BOTH IN RESIDENCE AT LEAST TWO YEARS; ONE NOT FULLY EMPLOYED LAST	
		coef	t-stat	coef	t-stat	coef	t-stat
	bmatch (no covariates)	0.0024	22.1000	0.0025	19.4000	0.0039	11.9453
Reside in same block	bmatch	-0.0036	-1.9448	-0.0034	-1.3395	0.0026	0.5058
Both high school drop out	hsd_hsd	0.0028	4.3859	0.0031	4.2075	0.0012	0.7640
Both high school graduate	hsg_hsg	0.0013	12.3505	0.0012	9.7509	0.0015	4.7894
Both college graduate	clg_clg	-0.0003	-3.5072	-0.0004	-3.5617	-0.0006	-2.1440
HS drop out - HS grad	hsd_hsg	0.0022	11.8281	0.0023	10.7450	0.0027	5.3064
HS drop out – College grad	hsd_clg	0.0006	2.9754	0.0008	3.5382	0.0003	0.4957
	bmatch* hsd_hsd	0.0006	0.3445	0.0000	-0.0237	-0.0004	-0.1009
	bmatch* hsg_hsg	0.0016	5.3192	0.0009	2.5293	0.0009	1.0225
	bmatch* clg_clg	0.0008	3.1667	0.0008	2.7995	0.0013	1.6422
	bmatch* hsd_hsg	0.0003	0.5780	0.0002	0.3339	-0.0015	-1.0496
	bmatch* hsd_clg	0.0000	-0.0794	0.0002	0.2966	0.0001	0.0873
Both White	wht_wht	-0.0014	-1.5649	-0.0001	-0.0907	0.0022	0.8276
Both Black	bl_bl	0.0014	1.2470	0.0006	0.4039	0.0058	1.8673
White – Black	bl_wht	-0.0019	-2.0054	-0.0009	-0.7286	0.0014	0.5376
White – Asian/Hispanic	ashi_wht	-0.0014	-1.5289	-0.0003	-0.2562	0.0015	0.5768
	bmatch* wht_wht	0.0012	0.6971	0.0055	2.2670	0.0030	0.6108
	bmatch* bl_bl	0.0021	0.9865	0.0031	1.1322	-0.0037	-0.6697
	bmatch* bl_wht	0.0010	0.5500	0.0024	0.9444	-0.0008	-0.1659
	bmatch* ashi_wht	0.0011	0.6107	0.0047	1.8153	-0.0026	-0.5087
Both have children	child_m	0.0008	6.9990	0.0007	5.9924	0.0013	4.4849
Both have children age 0-5	c05_05	-0.0004	-1.6713	-0.0007	-2.7317	-0.0014	-2.2624
Both have children age 6-12	c612_612	0.0014	6.9827	0.0017	8.1051	0.0020	4.1223
Both have children age 13-17	c1317_1317	0.0008	3.6580	0.0007	2.7617	0.0007	1.2205
Both have children age 18-24	c1824_1824	0.0001	0.4647	0.0001	0.3324	0.0006	0.9957
	bmatch* child_m	0.0008	2.4525	0.0000	-0.1228	-0.0008	-0.8606
	bmatch* c05_05	0.0024	3.8151	0.0014	1.9184	0.0041	2.3657
	bmatch* c612_612	-0.0006	-1.1366	-0.0012	-1.8165	-0.0014	-0.9718
	bmatch* c1317_1317	0.0043	6.2145	0.0041	5.4423	0.0043	2.5233
	bmatch* c1824_1824	-0.0009	-1.2592	-0.0003	-0.3792	-0.0006	-0.3503
Both age 25-34	a25_25	0.0001	0.8795	0.0002	1.2756	-0.0001	-0.2635
Both age 35-44	a35_35	-0.0003	-2.0681	-0.0003	-2.0085	-0.0003	-0.8766
Both age 45-59	a45_45	0.0006	3.7455	0.0007	3.9735	0.0011	2.5200
Age 25-34 and age 45-59	a25_45	0.0001	0.5039	0.0001	0.8261	-0.0002	-0.6150
Age 35-44 and age 45-59	a35_45	0.0002	1.9667	0.0003	2.2347	0.0005	1.5572

	bmatch*	a25_25	0.0015	4.5860	0.0002	0.5502	-0.0003	-0.2560
	bmatch*	a35_35	0.0019	4.9150	0.0017	3.8330	0.0021	1.9091
	bmatch*	a45_45	0.0020	4.5993	0.0013	2.5877	0.0033	2.5547
	bmatch*	a25_45	0.0005	1.6710	0.0001	0.2269	0.0009	0.8856
	bmatch*	a35_45	0.0017	5.2775	0.0011	2.9451	0.0017	1.7900
Both single male		sm_sm	-0.0027	-10.4690	-0.0031	-9.5824	-0.0026	-3.2741
Both single female		sf_sf	-0.0018	-7.5675	-0.0021	-7.2631	-0.0023	-3.3375
Single male–single female		sm_sf	-0.0023	-11.3198	-0.0027	-11.1270	-0.0022	-3.8427
Both married male		mm_mm	-0.0036	-22.2619	-0.0039	-21.5374	-0.0042	-8.5328
Married male–married female		mm_mf	-0.0030	-19.7063	-0.0032	-19.4269	-0.0034	-9.9138
Single male-married female		sm_mf	-0.0016	-8.5723	-0.0016	-7.7294	-0.0014	-3.0321
Single male-married male		sm_mm	-0.0029	-16.5575	-0.0032	-15.6640	-0.0033	-6.5973
Single female-married female		sf_mf	-0.0014	-7.9850	-0.0015	-7.4660	-0.0020	-4.5427
Single female-married male		sf_mm	-0.0030	-18.1066	-0.0034	-17.4136	-0.0036	-7.5944
	bmatch*	sm_sm	0.0037	5.8504	0.0013	1.5955	0.0001	0.0328
	bmatch*	sf_sf	0.0037	6.3320	-0.0001	-0.0731	-0.0005	-0.2572
	bmatch*	sm_sf	0.0026	5.1517	-0.0002	-0.3529	-0.0001	-0.0983
	bmatch*	mm_mm	0.0055	11.6692	0.0008	1.4624	-0.0001	-0.0803
	bmatch*	mm_mf	0.0039	9.0251	0.0005	0.9820	0.0015	1.4712
	bmatch*	sm_mf	0.0036	6.9085	0.0001	0.1250	0.0027	1.9925
	bmatch*	sm_mm	0.0042	8.4997	0.0010	1.6135	0.0022	1.5417
	bmatch*	sf_mf	0.0042	8.5433	0.0004	0.6222	0.0020	1.5635
	bmatch*	sf_mm	0.0035	7.3576	-0.0001	-0.2047	0.0008	0.5724
Combined length of residence		lngth	0.0000	7.9113	0.0001	5.0917	0.0001	3.1353
Minimum length of residence		lngth_min	0.0000	0.5654	0.0000	0.4951	0.0000	-0.0816
Moved within 5 year of each		lngth_within 5	0.0002	1.9233	0.0002	1.4490	0.0001	0.3189
	bmatch*	lngth	0.0000	0.0487	0.0000	-0.4146	-0.0001	-1.1278
	bmatch*	lngth_min	0.0000	-0.8033	0.0000	0.0262	0.0000	-0.0212
	bmatch*	lngth_within 5	0.0000	0.0358	0.0000	-0.0614	-0.0012	-1.0885
Block size (population)		blocksize	0.0000	1.7315	0.0000	1.5413	0.0000	3.1380
	bmatch*	blocksize	-0.000011	-4.3872	-0.000016	-4.8355	-0.000031	-3.6420
One not fully employed		1 not fully empd			0.0004	3.4467		
Two not fully employed		2 not fully empd			0.0021	5.2031		
	bmatch*	1 not fully empd			0.0008	2.4568		
	bmatch*	2 not fully empd			-0.0027	-2.2752		
Sample Size			4032109		2985691		578180	

TABLE 4

Sorting along Socio-Demographic Attributes

EDUCATION

	Block			Block Group			Tract		
	hsd	*hsg*	*clg*	*hsd*	*hsg*	*clg*	*hsd*	*hsg*	*clg*
hsd	22	49	28	17	49	35	15	49	37
hsg	9	51	40	9	48	43	9	48	43
clg	5	35	61	6	38	57	6	38	56

AGE

	Block			Block Group			Tract		
	a25	*a35*	*a45*	*a25*	*a35*	*a45*	*a25*	*a35*	*a45*
a25	47	28	25	41	31	28	41	31	29
a35	33	40	27	37	33	30	37	32	31
a45	32	29	39	36	32	33	36	32	32

RACE

	Block			Block Group			Tract		
	wh	*bl*	*as-hi*	*wh*	*bl*	*as-hi*	*wh*	*bl*	*as-hi*
white	97	2	2	96	2	2	96	2	2
black	40	53	7	46	46	8	49	43	8
asian/hisp	63	13	24	71	15	14	74	15	11

CHILDREN

	Block			Block Group			Tract		
	c05	*c612*	*c1317*	*c05*	*c612*	*c1317*	*c05*	*c612*	*c1317*
c05	40	35	16	22	22	16	21	21	20
c612	34	41	28	22	24	18	21	22	22
c1317	20	37	37	21	23	18	16	17	17

These figures show average exposure rates at each level. So, for example, the first few entries imply that on average high school dropouts live in Census Blocks that have 22% high school dropouts, 49% high school graduates, 28% college graduates.

The average ratio of the population of Blocks to Block Groups to Tracts is approximately 1:16:64

TABLE 5

Variable Name		Code	BLOCK GROUPS THAT ARE MOST HOMOGENEOUS IN TERMS OF EDUCATION coef	t-stat	BLOCK GROUPS THAT ARE MOST HOMOGENEOUS IN TERMS OF RACE coef	t-stat	BLOCK GROUPS THAT ARE MOST HOMOGENEOUS IN TERMS OF CHILDREN coef	t-stat
Reside in same block		bmatch (no covariates)	0.0024	14.2000	0.0024	14.6400	0.0023	12.8800
Reside in same block		bmatch	-0.0086	-2.9619	-0.0113	-3.2414	-0.0025	-0.8697
Both high school drop out		hsd_hsd	0.0028	2.5133	0.0022	2.1881	0.0026	2.4808
Both high school graduate		hsg_hsg	0.0012	6.4548	0.0015	9.4006	0.0010	5.3463
Both college graduate		clg_clg	-0.0002	-1.5896	-0.0004	-2.6264	-0.0003	-2.0153
HS drop out - HS grad		hsd_hsg	0.0022	6.4198	0.0022	7.6762	0.0021	6.4170
HS drop out – College grad		hsd_clg	0.0005	1.6379	0.0005	1.7303	0.0005	1.5683
	bmatch*	hsd_hsd	0.0014	0.4945	-0.0023	-0.8872	0.0010	0.4032
	bmatch*	hsg_hsg	0.0024	5.1000	0.0017	3.8140	0.0025	5.2488
	bmatch*	clg_clg	0.0011	2.8854	0.0017	4.5566	0.0005	1.3158
	bmatch*	hsd_hsg	-0.0003	-0.2950	0.0003	0.4216	0.0012	1.4594
	bmatch*	hsd_clg	-0.0004	-0.5061	-0.0004	-0.5040	-0.0010	-1.1357
Both White		wht_wht	-0.0007	-0.4516	-0.0043	-2.2872	-0.0021	-1.4041
Both Black		bl_bl	0.0044	2.4011	-0.0011	-0.4735	0.0017	0.9167
White – Black		bl_wht	-0.0010	-0.6842	-0.0047	-2.4660	-0.0020	-1.3154
White – Asian/Hispanic		ashi_wht	-0.0006	-0.4062	-0.0041	-2.1406	-0.0020	-1.3533
	bmatch*	wht_wht	0.0046	1.6752	0.0073	2.1632	-0.0035	-1.2910
	bmatch*	bl_bl	0.0067	2.0650	0.0120	3.0848	-0.0028	-0.8896
	bmatch*	bl_wht	0.0063	2.2113	0.0066	1.9159	-0.0037	-1.3369
	bmatch*	ashi_wht	0.0045	1.5645	0.0075	2.1605	-0.0013	-0.4504
Both have children		child_m	0.0007	4.0289	0.0008	4.9101	0.0007	3.4862
Both have children age 0-5		c05_05	-0.0005	-1.4413	-0.0002	-0.6817	-0.0009	-2.3239
Both have children age 6-12		c612_612	0.0012	3.6376	0.0015	5.0624	0.0013	3.7994
Both have children age 13-17		c1317_1317	0.0005	1.2507	0.0008	2.3660	-0.0001	-0.2296
Both have children age 18-24		c1824_1824	0.0002	0.4101	0.0001	0.4190	0.0000	0.0262
	bmatch*	child_m	0.0018	3.5992	0.0015	3.1362	0.0018	3.4121
	bmatch*	c05_05	0.0043	4.4280	0.0005	0.5227	0.0045	4.3204
	bmatch*	c612_612	-0.0008	-0.8502	-0.0011	-1.3412	-0.0027	-2.8537
	bmatch*	c1317_1317	0.0027	2.4545	0.0042	4.0096	0.0074	6.5487
	bmatch*	c1824_1824	-0.0028	-2.5229	0.0000	0.0192	-0.0012	-1.0619

Both age 25-34		a25_25	-0.0001	-0.2942	0.0001	0.2955	0.0001	0.3133
Both age 35-44		a35_35	-0.0003	-1.3007	-0.0004	-1.9990	-0.0002	-0.6888
Both age 45-59		a45_45	0.0004	1.4017	0.0010	4.1924	0.0008	2.9419
Age 25-34 and age 45-59		a25_45	0.0000	0.0218	0.0000	-0.1062	-0.0002	-1.1746
Age 35-44 and age 45-59		a35_45	0.0004	1.9394	0.0003	1.7628	0.0000	-0.2154
	bmatch*	a25_25	0.0026	5.2363	0.0009	1.8415	0.0019	3.7101
	bmatch*	a35_35	0.0018	3.0684	0.0016	2.8119	0.0026	4.1391
	bmatch*	a45_45	0.0021	3.0963	0.0010	1.4862	0.0018	2.4827
	bmatch*	a25_45	0.0005	0.9428	0.0002	0.5120	0.0014	2.8431
	bmatch*	a35_45	0.0016	3.0576	0.0009	1.9121	0.0023	4.2453
Both single male		sm_sm	-0.0019	-4.4423	-0.0030	-7.4728	-0.0025	-5.7258
Both single female		sf_sf	-0.0011	-3.0021	-0.0021	-5.9465	-0.0017	-4.3267
Single male–single female		sm_sf	-0.0019	-5.5979	-0.0028	-8.9740	-0.0023	-6.6765
Both married male		mm_mm	-0.0032	-12.2071	-0.0041	-16.9492	-0.0035	-12.3050
Married male–married female		mm_mf	-0.0025	-10.4047	-0.0036	-16.0370	-0.0028	-10.6305
Single male-married female		sm_mf	-0.0011	-3.6176	-0.0019	-6.8115	-0.0015	-4.7635
Single male-married male		sm_mm	-0.0022	-7.6939	-0.0033	-12.3466	-0.0026	-8.6094
Single female-married female		sf_mf	-0.0013	-4.3327	-0.0018	-6.8727	-0.0013	-4.2052
Single female-married male		sf_mm	-0.0025	-9.0605	-0.0033	-13.0483	-0.0026	-8.8776
	bmatch*	sm_sm	0.0046	4.7450	0.0048	5.1684	0.0048	4.8270
	bmatch*	sf_sf	0.0049	5.5184	0.0058	6.6737	0.0052	5.6083
	bmatch*	sm_sf	0.0034	4.3209	0.0043	5.5928	0.0048	5.8682
	bmatch*	mm_mm	0.0066	9.0569	0.0076	10.8836	0.0079	10.2533
	bmatch*	mm_mf	0.0057	8.5538	0.0061	9.5590	0.0051	7.3599
	bmatch*	sm_mf	0.0055	6.8161	0.0053	6.9682	0.0053	6.3862
	bmatch*	sm_mm	0.0055	7.1814	0.0069	9.3762	0.0066	8.2167
	bmatch*	sf_mf	0.0057	7.3866	0.0073	9.8486	0.0060	7.4814
	bmatch*	sf_mm	0.0040	5.4348	0.0055	7.7416	0.0049	6.3664
Combined length of residence		lngth	0.0000	2.5056	0.0000	2.4170	0.0000	1.2296
Minimum length of residence		lngth_min	0.0000	0.0582	0.0000	1.6759	0.0000	1.6396
Moved within 5 year of each		lngth_within 5	0.0002	0.9488	0.0000	0.1290	-0.0001	-0.2543
	bmatch*	lngth	0.0000	-0.0662	0.0000	-0.3866	0.0001	1.7889
	bmatch*	lngth_min	0.0000	-0.2410	0.0000	-0.0485	-0.0001	-1.7232
	bmatch*	lngth_within 5	-0.0002	-0.3773	-0.0005	-1.0095	0.0009	1.5411
Block size (population)		blocksize	0.0000	2.2500	0.0000	1.9565	0.0000	1.0744
	bmatch*	blocksize	-0.000014	-3.7346	-0.000011	-3.0192	-0.000013	-3.4245
Sample Size			1,460,630		1,784,927		1,386,891	

TABLE 6
Match Quality and Labor Market Outcomes

	Full Sample			Both in Residence Two Years		
	coef	t-stat	N	coef	t-stat	N
Labor Force Participation	0.0111	5.754	151572	0.0076	3.284	128797
Employment (Conditional on LFP)	-0.0002	-0.173	130231	0.0009	0.566	110433
Employed	0.0088	3.720	151572	0.0045	1.596	128797
Weeks Worked Last Year	0.5897	5.895	151572	0.3642	2.998	128797
Hours Worked Per Week	0.9112	10.511	151572	0.6439	6.149	128797
Log(Earnings)	0.0199	5.132	93053	0.0118	2.453	78200
Log(Wage)	0.0142	3.708	93053	0.0069	1.457	78200

Effect of a one standard deviation increase in match quality

TABLE 7
Match Quality and Labor Market Outcomes: Continued

	Both in Residence Two Years					Both in Residence Two Years; One Not Fully Employed		
	Match Quality		Match Quality * Not Fully Employed					
	coef	t-stat	coef	t-stat	N	coef	t-stat	N
Labor Force Participation	0.0018	0.917	0.0127	7.349	128797	0.0130	1.522	31778
Employment (Conditional on LFP)	-0.0029	-1.792	0.0243	13.715	110433	-0.0009	-0.081	14997
Employed	-0.0005	-0.210	0.0084	3.832	128797	0.0052	0.620	31778

Effect of a one standard deviation increase in match quality

TABLE 8

Match Quality and Labor Market Outcomes: Continued

	Homogeneous WRT Education			Homogeneous WRT Race			Homogeneous WRT Kids		
	coef	t-stat	N	coef	t-stat	N	coef	t-stat	N
Labor Force Participation	0.0100	5.366	151,572	0.0178	8.690	151,572	0.0095	4.474	151,572
Employment (Conditional on LFP)	-0.0003	-0.230	130,231	-0.0010	-0.692	130,231	-0.0017	-1.094	130,231
Employed	0.0084	3.654	151,572	0.0147	5.853	151,572	0.0051	1.940	151,572
Weeks Worked Last Year	0.5748	5.906	151,572	0.7872	7.363	151,572	0.4299	3.871	151,572
Hours Worked Per Week	0.8228	9.754	151,572	1.2200	13.170	151,572	0.8012	8.323	151,572
Log(Earnings)	0.0232	6.137	93,053	0.0256	5.956	93,053	0.0168	3.868	93,053
Log(Wage)	0.0174	4.654	93,053	0.0190	4.483	93,053	0.0109	2.556	93,053

Effect of a one standard deviation increase in match quality

Figure 1: Distribution of Blocks per Block Group

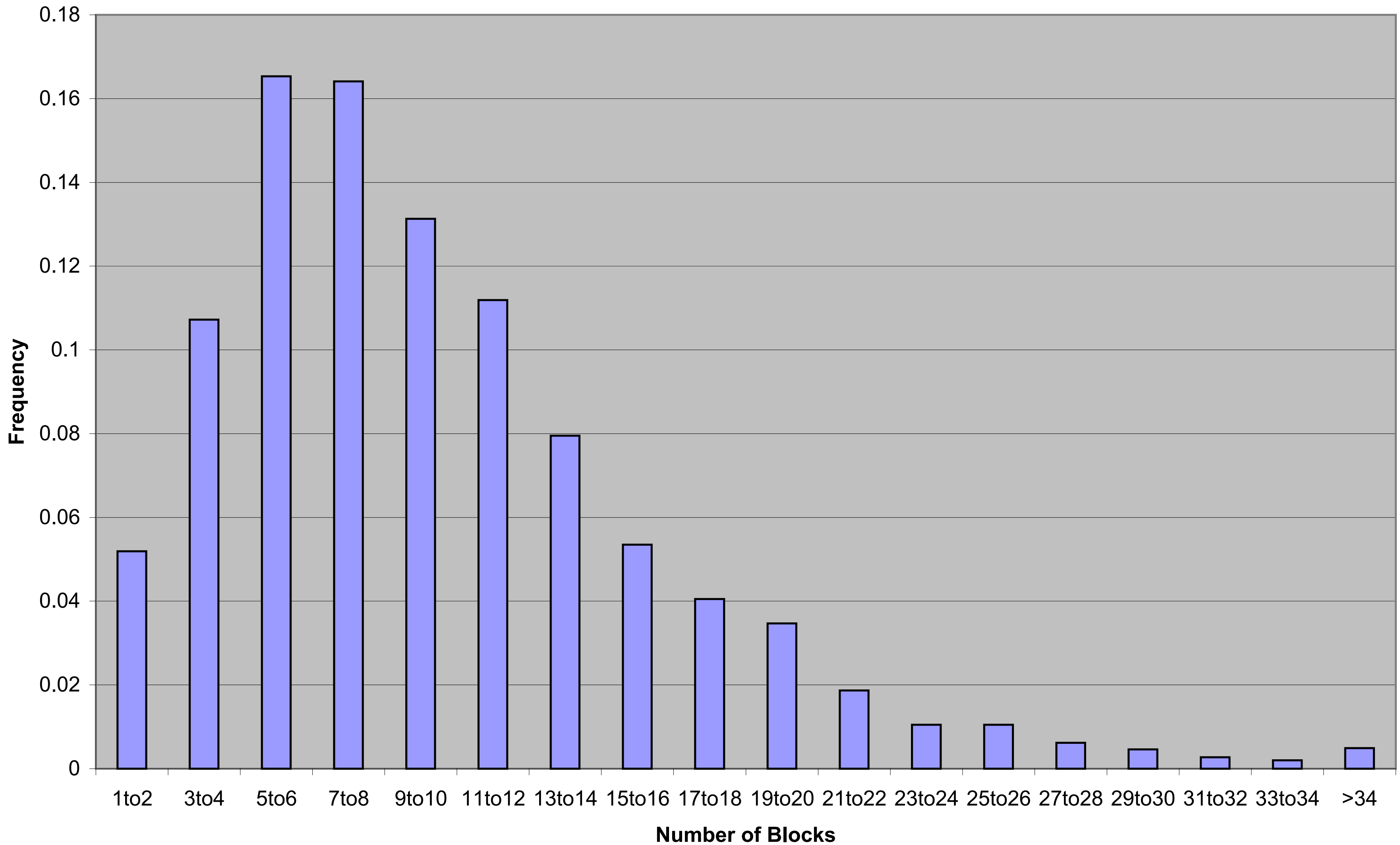

Figure 2: Distribution of Workers per Block