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Abstract

Using detailed data on friendship networks within neighborhoods, we investigate the importance of social interactions in one's own residential neighborhood in the demand for housing quality. We find evidence consistent with the presence of peer effects, especially for households living in urban areas. Our findings are in line with the prediction of a model where conformity preferences are the key element underlying economic outcomes that involve interactions with peers.

JEL No. A14, C21, D85, R21, Z13.

Key Words: Social Networks, Linear-In-Means Model, Spatial Autoregressive Model, Social Norms

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1 Introduction

There is an increasing recognition in economics that social interactions play a major role in explaining a range of individual behaviors, as well as the individual's valuation of both the decision and the resulting outcome.[1] Peer effects have been indicated as important determinants of behavior in a variety of contexts. Examples include education, crime, labor market, fertility, obesity, productivity, participation in welfare programs, risky behavior, to mention a few (for surveys, see Glaeser and Scheinkman, 2001; Moffitt, 2001; Durlauf, 2004; Ioannides and Loury, 2004; Jackson, 2009; Ioannides, 2012). In many social phenomena peer effects stems from preferences for conformity. Conformism is the idea that the easiest and hence best life is attained by doing one's very best to blend in with one's surroundings, and to do nothing eccentric or out of the ordinary in any way. In an economy with conformity preferences peer effects are viewed as a social norm and individuals pay a cost from deviating from this norm. Different aspects of conformism and social norms have been explored from a theoretical point of view. To name a few, (*i*) peer pressures and partnerships (Kandel and Lazear 1992) where peer pressure arises when individuals deviate from a well-established group norm, e.g. individuals are penalized for working less than the group norm, (*ii*) religion (Iannaccone 1992, Berman 2000) since praying is much more satisfying the more participants there are, (*iii*) social status and social distance (Akerlof 1980, 1997, Bernheim 1994, among others) where deviations from the social norm (average action) imply a loss of reputation and status, (iv) crime (Glaser et al. 1996, Patacchini and Zenou 2012) where individual wants to minimize the social distance between her crime level and that of her reference group.

In this paper we study whether conformist behavior affects the individual demand for housing quality. The literature on social interactions in the housing market is extremely limited (see Ioannides, 2012 for a critical survey) and presents two important challenges: *(i)* to disentangle peer effects from neighborhood effects; *(ii)* to explain *how* peers influence each other, i.e. the mechanism generating such social interactions.

The study of peer effects in housing decisions is, however, paramount for policy purposes.

[1]The integration of models of social interactions within economic theory is an active and interesting area of research. See the recent *Handbook of Social Economics* (Benhabib, Bisin and Jackson (eds), 2011)

One of the reason suggesting government intervention in the housing market is inefficiency in housing consumption. Housing renovations improve not only one's own property but also neighbors' property values. However, this externality is not internalized in the individual's calculation of whether or not to undertake an improvement. As a results, the marginal social benefits of the improvement exceed the private marginal costs, and the property owner is likely to invest less than a socially efficient amount. Under this perspective, the existence of peer effects could overcome the underprovision of local public goods (Rosen 1985).

Ioannides and Zabel (2000) are the first to consider housing demand with neighborhood effects. They use the neighborhood cluster level information provided in a special sample of the American Housing Survey to measure neighborhood influences.[2]

Our analysis uses detailed data on friendship networks within residential neighborhoods to measure peer groups more precisely than previous studies and elaborates on a conformism model, presented by Patacchini and Zenou (2012), to guide the interpretation of the results.[3] More precisely, borrowing from Patacchini and Zenou (2012), we first present a social network model of peer effects that show how conformism affects the demand for housing quality. We then take the model to the data by using the U.S. National Longitudinal Survey of Adolescent Health (AddHealth). This data contains unique information on friendship relationships among a representative sample of students from U.S. high school teenagers together with residential neighborhood identifiers. The survey design also includes a questionnairre administered to the interviewers which collects information on the type and quality of the respondent's residential building and area of residence. These questions are thus informative of each student's household decisions about house maintenance, repair and renovation. Under the assumption that the children's social contacts in the neighborhood are a good approximation of their parents' social contacts, these data are thus able to shed some light on the importance of social interactions in the demand for housing quality.

Empirical tests of models of social interactions are quite problematic. The issues that

[2] Ioannides and Zabel (2008) introduce neighhborhood choice to the analysis of the housing demand with neighborhood effects.

[3] The constraints imposed by the available disaggregated data force many studies to analyze peer effects at a quite aggregate and arbitrary level, such as at the neighborhood level (see, e.g. the recent literature by Durlauf, 2004, Ioannides and Topa, 2010, and Ioannides, 2011).

render the identification and measurement of peer effects quite difficult are well known: : (*i*) reflection, which is a particular case of simultaneity (Manski, 1993) and (*ii*) endogeneity, which may arise for both peer self-selection and unobserved common (group) correlated effects.

In this paper, we exploit the architecture of social networks to overcome this set of problems and to achieve the identification of endogenous peer effects. More specifically, in social networks, each agent has a different peer-group, i.e. different friends with whom each teenager directly interacts. This feature of social networks guarantees the presence of excluded friends from the reference group (peer-group) of each agent, which are, however, included in the reference group of his/her best (direct) friends. This identification strategy is similar in spirit to the one used in the standard simultaneous equation model, where at least one exogenous variable needs to be excluded from each equation. In addition, because we observe the precise patterns of social interactions within neighborhoods (i.e. different peer groups over neighborhoods), we can include neighborhood fixed effects in the empirical specification of the model. By doing so, we are thus able to disentangle peer effects from the presence of neighborhood unobserved factors affecting both individual and peer behaviors. Such factors might be important omitted variables driving the sorting of agents into neighborhoods.

This strategy leads to the following main findings: conformity plays an important role in the individual demand for housing quality. If we consider an average group of 4 best friends (linked to each other in a network), a standard deviation increase in the demand for housing quality of each of the peers translates into a roughly 15 percent of a standard deviation increase in the individual demand for housing quality. This effect is larger in urban areas and virtually zero in non urban areas.

The analysis of peer effects is, however, a complex issue and our analysis obviously has some limitations. Firstly, our model is only one of the possible mechanisms generating such externalities. It is not, however, rejected by our data and it serves to highlight the importance of non market interactions in explaining individual demand for housing quality. Secondly, in the absence of experimental data, one can never be sure to have captured all the behavioral intricacies that lead individuals to associate with others. In addition, our data provides an imprecise measure of the demand for housing quality. Nevertheless, by using both within-and between-network variation and by taking advantage of the unusually large information on teenagers' behavior provided by our dataset, our analysis is a valid attempt to overcome the empirical difficulties.

The rest of the paper unfolds as follows. In the next section, we present the theoretical framework that helps us to understand how social contacts can influence individual demand for housing quality. Section 3 describes the data and the empirical strategy. In Section 4, we present our empirical results. Section 5 checks the sensitivity of our results to measurement errors in peer groups. Finally, Section 6 concludes.

2 Theoretical framework

Following Patacchini and Zenou (2012), we present a social network model of peer effects with conformity preferences for the demand of housing quality.

There are $N = \{1, \ldots, n\}$ individuals in the economy distributed among K residential neighborhoods. Let n_k be the number of individuals in the kth neighborhood, so that $N = \sum_{k=1}^{K} n_k$. Each neighborhood contains several networks.

The network The adjacency matrix $\mathbf{G} = [g_{ij}]$ of a network $\mathbf{g}$ keeps track of the direct connections in this network. Here, two players i and j are directly connected (i.e. best friends) in $\mathbf{g}$ if and only if $g_{ij} = 1$, and $g_{ij} = 0$, otherwise. Given that friendship is a reciprocal relationship, we set $g_{ij} = g_{ji}$.[4] We also set $g_{ii} = 0$. The set of individual i's best friends (direct connections) is: $N_i(\mathbf{g}) = \{j \neq i \mid g_{ij} = 1\}$, which is of size g_i (i.e. $g_i = \sum_{j=1}^{n} g_{ij}$ is the number of direct links of individual i). This means in particular that, if i and j are best friends, then in general $N_i(\mathbf{g}) \neq N_j(\mathbf{g})$ unless the graph/network is complete (i.e. each individual is friend with everybody in the network). This also implies that groups of friends may overlap if individuals have common best friends. To summarize, the *reference group* of each individual i is $N_i(\mathbf{g})$, i.e. the set of his/her best friends, which does not include him/herself.

[4]This is not an important assumption since all our theoretical results hold even when $g_{ij} \neq g_{ji}$. We discuss this issue in Section 5.

Preferences Individuals in network $\mathbf{g}$ decide how much effort to exert in home maintenance, repair and renovation. We denote by y_i the effort level of individual i in network $\mathbf{g}$ and by $Y = (y_1, ..., y_n)'$ the population effort profile in network $\mathbf{g}$. Denote by $\overline{y}_i$ the average effort of individual i's best friends. It is given by:

$$\overline{y}_i = \frac{1}{g_i} \sum_{j=1}^{n} g_{ij} y_j \tag{1}$$

Each agent i in neighborhood k selects an effort $y_{i,k} \geq 0$, and obtains a payoff $u_{i,k}(Y, \mathbf{g})$ that depends on the effort profile Y and on the underlying network $\mathbf{g}$, in the following way:

$$u_{i,k}(Y, \mathbf{g}) = (a_{i,k} + \eta_k + \varepsilon_{i,k})\ y_{i,k} - \frac{1}{2} y_{i,k}^2 - \frac{d}{2} (y_{i,k} - \overline{y}_{i,k})^2 \tag{2}$$

where $d > 0$ and $\overline{y}_{i,k} = \overline{y}_i$ (as the neighborhoods do not overlap). The benefit part of this utility function is given by $(a_{i,k} + \eta_k + \varepsilon_{i,k})\ y_{i,k}$ while the cost is $\frac{1}{2} y_{i,k}^2$; both are increasing in own effort $y_{i,k}$. In this part, $a_{i,k}$ denotes the agent's ex-ante *idiosyncratic heterogeneity,* which is assumed to be deterministic, perfectly *observable* by all individuals in the network and corresponds to the observable characteristics of individual i (e.g. sex, race, age, parental education) and to the observable average characteristics of individual i's best friends, i.e. average level of parental education of i's friends, etc. (contextual effects). To be more precise, $a_{i,k}$ can be written as:

$$a_{i,k} = \sum_{m=1}^{M} \beta_m x_{i,k}^m + \frac{1}{g_i} \sum_{m=1}^{M} \sum_{j=1}^{n} \theta_m g_{ij}\, x_{j,k}^m \tag{3}$$

where x_i^m is a set of M variables accounting for observable differences in individual characteristics of individual i, and β_m, θ_m are parameters. In the utility function (2) η_k denotes the unobservable neighborhood characteristics and $\varepsilon_{i,k}$ is an error term, meaning that there is some uncertainty in the benefit part of the utility function. Both η_k and $\varepsilon_{i,k}$ are observed by the individuals but not by the researcher. The second part of the utility function $\frac{d}{2} (y_{i,k} - \overline{y}_{i,k})^2$ reflects the influence of friends' behavior on own action. It is such that each individual wants to minimize the *social distance* between herself and her reference group, where d is the parameter describing the *taste for conformity.* Here, the individual loses utility $\frac{d}{2} (y_{i,k} - \overline{y}_{i,k})^2$ from failing to conform to others. This is the standard way economists have been modelling conformity (see, among others, Akerlof, 1980, Bernheim, 1994, Kandel and Lazear, 1992, Akerlof, 1997, Fershtman and Weiss, 1998; Patacchini and Zenou, 2012). In the context of the demand for housing quality, a taste for conformity captures the idea of "keeping up with the Joneses," where individuals view their neighbors' decisions about maintenance, repair and renovation, and do their best to keep up by making similar decisions.[5] The social norm can be interpreted as friends' social status, as signalled by house quality.

Observe that the social norm here captures the differences between individuals due to network effects. It means that individuals have different types of friends and thus different reference groups $\overline{y}_{i,k}$. As a result, the social norm each individual i faces is endogenous and depends on her location in the network as well as the structure of the network.

Nash equilibrium

In this game where agents choose their effort level $y_{i,k} \geq 0$ simultaneously, there exists a unique Nash equilibrium (Patacchini and Zenou 2012) given by:

$$y_{i,k}^{*} = \phi \frac{1}{g_i} \sum_{j=1}^{n_k} g_{ij} y_j^{*} + (1-\phi)\left(a_{i,k} + \eta_k + \varepsilon_{i,k}\right) \tag{4}$$

where $\phi = d/(1+d)$. The optimal effort level depends on the individual ex ante heterogeneity ($a_{i,k}$), on the unobserved neighborhood characteristics (η_k) and it is increasing with the average effort of the reference group. This means that the more well kept the houses of one's friends are, the more the individual will provide effort in the upkeep of her own house.

3 Data and empirical strategy

3.1 Data

Our data source is the National Longitudinal Survey of Adolescent Health (AddHealth), which contains detailed information on a nationally representative sample of 90,118 students in

[5] Morris and Winter (1975, 1978) introduced the notion of "housing deficit" to conceptualize residential (dis)satisfaction. In their housing adjustment model of residential mobility, they theorize that individuals judge their housing conditions according to predefined norms, which are dictated by societal living standards or rules.

roughly 130 private and public schools, entering grades 7-12 in the 1994-1995 school year.[6] Every pupil attending the sampled schools on the interview day is asked to complete a questionnaire (*in-school survey*) containing questions on respondents' demographic and behavioral characteristics, education, family background and friendship. A subset of adolescents selected from the rosters of the sampled schools, about 20,000 individuals, is then asked to complete a longer questionnaire containing questions relating to more sensitive individual and household information (*in-home survey* and parental data). AddHealth contains unique information on friendship relationships, which is crucial for our analysis. The friendship information is based upon actual friends nominations. Pupils were asked to identify their best friends from a school roster (up to five males and five females).[7] A link exists between two friends if at least one of the two individuals has identified the other as his/her best friend.[8] Importantly, these data also contain each respondent's residential neighborhood identifier. Hence, it is possible to reconstruct the geometry of the friendship networks within each neighborhood. Neighborhoods are defined as census tracts. By matching the identification numbers of the friendship nominations to respondents' identification numbers, one can also obtain information on the characteristics of nominated friends.

Besides information on family background, school quality and area of residence, the AddHealth data enclose information on the interviewer's remarks after having visited the students' house for the in-home interview. We use this information to construct our dependent variable $y_{i,k}$. Specifically, the interviewer is asked: "How well kept is the building in which the respondent lives?", with possible answers "very poorly kept (needs major repairs)", "poorly kept (needs minor repairs)", "fairly well kept (needs cosmetic work" and "very well kept", coded 1 to 4.[9] The interviewer questionnaire also asks to describe the immediate area or street (one

[6] For a detailed description of the survey and data, see the AddHealth website at: http://www.cpc.unc.edu/projects/addhealth.

[7] The limit in the number of nominations is not binding, not even by gender. Less than 1 percent of the students in our sample show a list of ten best friends, less than 3 percent a list of five males and roughly 4 percent name five females. On average, they declare to have 5.65 friends with a small dispersion around this mean value (standard deviation equal to 1.41).

[8] Note that, when an individual i identifies a best friend j who does not belong to the surveyed schools, the database does not include j in the network of i; it provides no information about j. However, in the large majority of cases (more than 94%), students tend to nominate best friends who are students in the same school and thus are systematically included in the network (and in the neighborhood patterns of social interactions).

[9] The residential building concides with the residential house in the majority of the cases (more than 75% of

block, both sides) where the respondent lives. We use this question to investigate whether peer effects in the demand for housing quality differ between urban and non urban areas.[10] Using the corresponding information for nominated friends, we are able, for each individual i in neighborhood k, to calculate the average effort $\overline{y}_{i,k}$ of his/her peer group. Excluding the individuals with missing or inadequate information, we obtain a final sample of 10,431 students distributed over 451 networks. Table A1 in the Data Appendix gives the definition of the variables used in our study as well as their descriptive statistics. Among the individuals selected in our sample, 46 percent are female and 17 percent are non whites. The average parental education is high-school graduate. Roughly 10 percent have parents working in a managerial occupation, another 10 percent in the office or sales sector, 25 percent in a professional/technical occupation, and roughly 20 percent have parents in manual occupations. Roughly 65 percent of our individuals come from a household with two married parents and from a household of about four people on average. More than 60 percent of our adolescents have an active social life, as measured by the participation to clubs, organization or teams.

3.2 Empirical strategy

Guided by the behavioral mechanism formalized in Section 2, our aim is to assess the actual empirical relationship between the neighbors' effort $\overline{y}^*_{i,k}$ and individual effort level $y^*_{i,k}$.

Let $\bar{r}_k$ be the total number of networks in neighborhood k, n_{rk} be the number of individuals in the rth network g_r in neighborhood k, and let $n_k = \sum_{r=1}^{\bar{r}_k} n_{rk}$ be the total number of sample observations in neighborhood k. The empirical equivalent of the first order conditions of our network model of peer effects (equation 4) is given by:

$$y_{i,r,\kappa} = \phi \frac{1}{g_{i,r}} \sum_{j=1}^{n_{r\kappa}} g_{ij,r}\, y_{j,r,k} + \sum_{m=1}^{M} \beta_1^m x_{i,r,\kappa}^m + \frac{1}{g_{i,r}} \sum_{m=1}^{M} \sum_{j=1}^{n_{r\kappa}} \theta_m g_{ij,r} x_{j,r,\kappa}^m + \eta_k + \varepsilon_{i,r,k} \qquad (5)$$

where $y_{i,r,\kappa}$, is the housing quality of the household of student i in network r and residing in

the students live in semidetached or detached single family houses). The results remain largely unchanged if we exclude individuals living in apartment buildings.

[10] Urban areas mainly indicate residential only areas, whereas non urban areas includes rural, suburban, mostly retail and mostly industrial areas.

neighborhood κ, $x^m_{i,r,\kappa}$ (for $m = 1, ..., M$) is the set of M control variables, $g_{i,r} = \sum_{j=1}^{n_{r\kappa}} g_{ij,r}$ is the number of direct links of i, $\sum_{j=1}^{n_{r\kappa}} \left(g_{ij,r} x^m_{j,r,\kappa} \right) / g_{i,r}$ is the set of the average values of the M controls of i's direct friends (i.e. contextual effects). As stated in the theoretical model, $\sum_{m=1}^{M} \beta_1^m x^m_{i,r,\kappa} + \frac{1}{g_{i,r}} \sum_{m=1}^{M} \sum_{j=1}^{n_{r\kappa}} \theta_m g_{ij,r} x^m_{j,r,\kappa}$ reflects the ex ante idiosyncratic heterogeneity of each individual i, and our measure of *taste for conformity* or *strength of peer effects* is captured by the parameter ϕ (in the theoretical model $\phi = d/(1+d)$). To be more precise, $\phi = d/(1+d)$ measures the taste for conformity relative to the direct, time or psychological costs of home repair and maintenance. Finally, η_k captures neighborhood specific unobserved factors (constant over individuals in the same network), which might be correlated with the regressors, and $\varepsilon_{i,k,r}$ is a white noise error. A precise description of the variables included and the corresponding descriptive statistics are contained in the Data Appendix to this paper (Table A.1, Appendix 1).

A number of papers have dealt with the identification and estimation of peer effects in model (5) using network data (e.g. Clark and Loheac 2007; Lee 2007; Bramoullè et al. 2009; Liu and Lee, 2010, Calvó-Armengol et al., 2009; Lin, 2010; Lee et al., 2010, Patacchini and Zenou, 2012). The common strategy is to exploit the architecture of network contacts to disentangle endogenous from exogenous (contextual) effects.[11] Model (5) can then be estimated using an Instrumental Variables or Maximum Likelihood approach. We follow this literature and estimate our conformism model using Maximul Likelihood (as in Patacchini and Zenou, 2012).[12]

In model (5), ϕ represents *the endogenous effects*, where an agent's choice/outcome may depend on those of his/her friends on the same activity; and θ represents *the contextual effect*, where an agent's choice/outcome may depend on the exogenous characteristics of his/her friends. The vector of neighborhood fixed effects η_k captures *the correlated effect* where agents

[11] It is well known that endogenous and contextual effects cannot be separately identified in a linear-in-means model due to *the reflection problem*, first formulated by Manski (1993). In social networks data, *the intransitivity in social connections* provides an exclusion restriction to identify endogenous and contextual effects (see, e.g. Bramoullè et al. 2009).

[12] In the spatial econometrics literature, model (5) is the so-called *spatial lag model* or *mixed-regressive spatial autoregressive model* (Anselin, 1988) with the addition of a neighborhood-specific component of the error term. Once the variables are transformed in deviations from the neighborhood-specific means, a Maximum Likelihood approach (see, e.g. Anselin, 1988) allows us to estimate jointly $\widehat{\boldsymbol{\beta}}$, $\widehat{\gamma}$, and $\widehat{\phi}$.

in the same network may behave similarly as they have similar unobserved individual characteristics or they face a similar environment.

4 Empirical results

The maximum likelihood estimation results of model (5) are reported in Table 1 (first column).[13] The table shows that the estimated coefficient of ϕ, which measures the *taste for conformity*, is statistically significant and has a positive sign. In a group of two friends, a standard deviation increase in the demand for housing quality of the friend translates into a roughly 3.5 percent increase of a standard deviation in the individual demand for housing quality. If we consider an average group of 4 best friends (linked to each other in a network), a standard deviation increase in the level of activity of each of the peers translates into a roughly 15 percent increase of a standard deviation in the individual level of activity. This is a non-negligible effect, especially given our long list of controls. This evidence thus supports our theoretical framework predicting a relevant role of peers and conformity to peers' behavior in shaping housing-related decisions.

[*Insert Table* 1 *here*]

In order to further our understanding of the results, we estimate model (5) for individulas living in urban and non urban areas separately. The results are collected in the last two columns of Table 1. The basic idea of our theoretical model is that agents' behavior in terms of housing quality choices is driven by their desire to reduce the discrepancy between their own house quality and that of their reference group (i.e. their best friends). Social interactions are the law of motion of this mechanism. If this is the behavioral mechanism at work, then we should observe in our data that peer effects are stronger in urban areas, i.e. where social interactions are more intense. Indeed, people living in urban areas have richer social opportunities than people living in non urban areas, and they may get more benefit from conforming to the

[13] When the model is estimated with an increasing set of controls (i.e. by adding the different groups listed in Table A.1) the value of $\widehat{\phi}$ decreases, thus indicating we are capturing important confounding factors. However, the qualitative results remain unchanged. The complete list of estimation results are available upon request.

standards of their social group. It appears that peer effects are stronger for individuals living in urban areas. They are not even statistically significant for individuals living in non urban areas. Hence, this evidence lends further support to the theoretical mechanism presented in Section 3.

5 Robustness check: Undirected vs directed networks

Our theoretical model and consequently our empirical investigation assume, so far, that friendship relationships are symmetric, i.e. $g_{ij} = g_{ji}$. In this Section, we check how sensitive our results are to such an assumption, i.e. to a possible measurement error in the definition of the peer group. Indeed, our data make it possible to know exactly who nominates whom in a network and we find that 12 percent of relationships in our dataset are not reciprocal. Instead of constructing undirected network, we will now focus on the analysis of directed networks.

In the language of graph theory, in a directed graph, a link has two distinct ends: a head (the end with an arrow) and a tail. Each end is counted separately. The sum of head endpoints count toward the *indegree* and the sum of tail endpoints count toward the *outdegree*. Formally, we denote a link from i to j as $g_{ij} = 1$ if j has nominated i as his/her friend, and $g_{ij} = 0$, otherwise. The indegree of student i, denoted by g_i^+, is the number of nominations student i receives from other students, that is $g_i^+ = \sum_j g_{ij}$. The outdegree of student i, denoted by g_i^-, is the number of friends student i nominates, that is $g_i^- = \sum_j g_{ji}$. We can thus construct two types of directed networks, one based on indegrees and the other based on outdegrees. Observe that, by definition, while in undirected networks the adjacency matrix $\mathbf{G} = [g_{ij}]$ is *symmetric*, in directed networks it is *asymmetric*.

From a theoretical point of view, the symmetry of $\mathbf{G}$ does not play any explicit role and thus all the results remain valid with a non-symmetric $\mathbf{G}$ (Patacchini and Zenou, 2012). Turning to the empirical analysis, we report in Tables 2 and 3 the results of the estimation of model (5) when the directed nature of the network data is taken into account. It appears that our results are only minimally affected in both tables. The estimated peer effects remain positive and statistically significant.

[*Insert Tables* 2 and 3 *here*]

6 Concluding remarks

Housing is a composite commodity that satisfies dwelling needs, but it also provides other intangibles such as security, access to jobs and social status. The diversity in individual preferences along these different dimensions leads to a large heterogeneity in the revealed behavior, that is, the demand for housing quality. An understanding of the importance of non market factors in housing related decisions is crucial to design more effective housing programs.

Although our results are not conclusive on the determinants of non functional demand for housing services, they suggest that social comparisons originated in one's own residential neighbohood are important in shaping the demand for housing quality. There is little doubt that individuals' satisfaction with a given behavior also depends on what one achieves in relative terms, i.e. compared to other individuals. A "conspicuous consumption" (Veblen, 1899) or a "bandwagon effect" are cases where the commodity serves the purpose of social belonging or status definition (Leibenstein, 1950). For most individuals, housing is the largest consumption and investment item of their life. A discrepancy between current and desired housing needs may create stress or dissatisfaction through migration or remodelling and thus distraction of resources from alternative investments such as education. Individuals' subjective evaluation of their housing forms the basis of demand for public action. This suggests that an effective policy should take into account the group interactions it stimulates.

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Table 1: Maximum likelihood estimation results

Dependent variable: house quality

Variable	All sample	Urban areas	Non urban areas
Conformism / peer effects (ϕ)	0.0423**	0.0587***	0.0360
	(0.0205)	(0.0219)	(0.0239)
Individual socio-demographic variables	yes	yes	yes
Family background variables	yes	yes	yes
Contextual effects	yes	yes	yes
Neighborhood fixed effects	yes	yes	yes
pseudo-R^2	0.6910	0.6677	0.6521

Notes:

- Estimated coefficients and standard errors (in parentheses) are reported
- Estimation using SpaceStat v1.93 (Anselin, 1995).
- Control variables are those listed in Table A.1
- Regressions include weights to control for the AddHealth survey design
- **, *** indicate statistical significance at the 5 and 1 percent levels

Table 2: Maximum likelihood estimation results

Dependent variable: house quality

- Directed networks using indegrees -

Variable	All sample	Urban areas	Non urban areas
Conformism / peer effects (ϕ)	0.0469**	0.0613**	0.0401
	(0.0279)	(0.0284)	(0.0310)
Individual socio-demographic variables	yes	yes	yes
Family background variables	yes	yes	yes
Contextual effects	yes	yes	yes
Neighborhood fixed effects	yes	yes	yes
pseudo-R^2	0.5704	0.5808	0.5676

Notes:

- Estimated coefficients and standard errors (in parentheses) are reported
- Estimation using SpaceStat v1.93 (Anselin, 1995).
- Control variables are those listed in Table A.1
- Regressions include weights to control for the AddHealth survey design
- **, *** indicate statistical significance at the 5 and 1 percent levels

Table 3: Maximum likelihood estimation results

Dependent variable: house quality

- Directed networks using outdegrees -

Variable	All sample	Urban areas	Non urban areas
Conformism / peer effects (ϕ)	0.0515**	0.0606**	0.0372
	(0.0251)	(0.0286)	(0.0304)
Individual socio-demographic variables	yes	yes	yes
Family background variables	yes	yes	yes
Contextual effects	yes	yes	yes
Neighborhood fixed effects	yes	yes	yes
pseudo-R^2	0.6145	0.6467	0.6252

Notes:

- Estimated coefficients and standard errors (in parentheses) are reported
- Estimation using SpaceStat v1.93 (Anselin, 1995).
- Control variables are those listed in Table A.1
- Regressions include weights to control for the AddHealth survey design
- ** indicates statistical significance at the 5 percent level