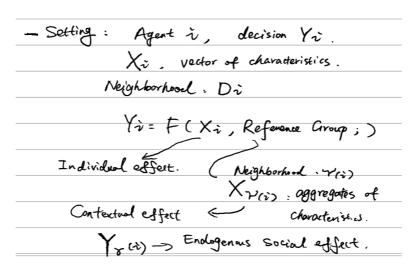
Lecture 1. Introduction

- Why do we care about social interactions in economic decisions?
 Because there are always direct interactions between agents (such as individuals, organizations, firms, and governments), and influences do not go through market (for example not reflected by prices)
- Action of an individual as a function of own characteristics, characteristics of his/her neighborhood and of actions of her neighbors, peers, etc



- Neighborhoods are exogenous or endogenous
- Empirical observations can motivate network related explanations.

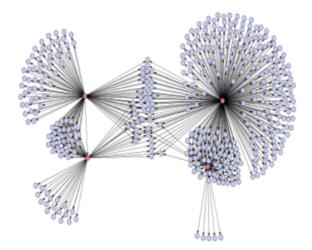


Figure: When people are influenced by the behaviors of their neighbors in the network, the adoption of a new product or innovation can cascade through the network structure. Here, e-mail recommendations for a Japanese graphic novel spread in a kind of informational or social contagion. (Leskovec et al. 2007)

- Visual representation of social networks
- Social graph (a 0-1 graph or different weight)
- Adjacency matrix representation (or sociomatrix)
- The social Interactions and the network Approach
- Interactions: social effect is defined in reference to a population of peers, groups of peers, neighbors etc., residential or based on another definition.
- Networks: social effects in reference to specific individuals in a social context with a defined social position. Example of spread of microfinance uptake in an Indian village, discussed in one of the readings, but not discussed in class.

Lecture 2. Manski typology and Adjacency Matrix

- Distinguishing effects:
- Throughout the course, we will be aiming at distinguishing to what an extent a person's or a firm's decision is due to following her peers, or influenced by the characteristics, in addition to own reasons and characteristics that propel some to act.
- Manski typology of social interactions:

Typology of social interactions, commonly referred to as the Manski typology: Y_i : Decision of i; X_i ,: characteristics of i, like age, education, gender, health, ethnic origin, etc; $\nu(i)$: the sets of neighbors of i; $X\nu(i)$: the characteristics of the neighbors; $Y\nu(i)$: the decisions of the neighbors. Then, schematically, we have:

$$Y_i = F(X_i; X\nu(i); Y\nu(i)).$$

The neighbors could be residential neighbors, coworkers, classmates, etc., or connections in a social network, like your Facebook.com friends.

- We think of individual making decisions based on the expectations of the decisions of their neighbors
- Xv(i) is the contextual effectr, Yv(i) is the endogenous social effect
- Adjacency matrix.

Consider a set of individuals: $\mathcal{I} = \{1, 2, 3, ..., I\}$. The numbers can be names.

$$a_{ij} = 1$$
, if i is connected with $j = 0$, otherwise.

Adjacency matrix (or sociomatrix) defined as:

$$\mathbf{A} = [a_{ij}]$$

It is a matrix of 0's and 1's. But, we can also have different weights, in which case we have a weighted graph.

Lecture 3. Sacerdote (2001)

- Sacerdote (2001)
- This paper uses a unique data set to measure peer effects among college roommates. Freshman year roommates and dormmates are randomly assigned (a key advantage to the researcher) at Dartmouth College.
- The conclusion is that peers have an impact on grade point average and on decisions to join social groups such as fraternities.
- Residential peer effects are markedly absent in other major life decisions such as choice of college major.
- Peer effects in GPA occur at the individual room level, whereas peer effects in fraternity membership occur both at the room level and the entire dorm level.
- Sacerdote Equation

To see what it means that the GPAs of roommates are simulataneously estimated, consider that each student i has a single roommate j. Then we have:

$$GPA_i = \delta + \alpha \times ACA_i + \beta \times ACA_j + \gamma \times GPA_j + \epsilon_i$$
.

$$GPA_i = \delta + \alpha \times ACA_i + \beta \times ACA_i + \gamma \times GPA_i + \epsilon_i$$
.

Since i and j are roommates, we can solve this system of two simultaneous equations and get [see Sacerdote, Eq. 1, 2]:

$$GPA_i = \frac{1}{1 - \gamma^2} [(1 + \gamma)\delta] + \frac{1}{1 - \gamma^2} (\alpha + \gamma\beta) ACA_i + \frac{1}{1 - \gamma^2} (\beta + \gamma\alpha) ACA_j + \epsilon_i'.$$

Note that the coefficients of ACA_i and ACA_j are functions of all the parameters of the problem.

Suppose that $\gamma = 0$: No endogenous social effect. Thus:

$$GPA_i = \delta + \alpha ACA_i + \beta ACA_j + \epsilon'_i$$
.

ACAs are exogenous variables, GPA are endogenous. Thus we can see the coefficients of GPA as endogenous social effects.

- Problems: (1) GPA is not exogenous and not independend of ACA, reflection problem
 (2) Not randomly assigned
- What we learned: (1) Social Influences is present but we do not know its nature
 - (2) Proximity due to living in a dorm matters
 - (3) Social effects in social outcomes are more volatile

Lecture 4. Arcidiacono and Nicholson (2005) and Ioannides (2002)

- Arcidiacono and Nicholson (2005)
- Students were chosen, did not choose one another (matching)
- What we learned:
- Academic performance on Board scores: They find positive peer effects (school average performance in MCAT verbal on student's board score), but it vanishes after controlling school fix effect.
- The peer groups may be **race-based or gender based.**The coefficient of (MCAT verbal * female) is significant. Which suggests peer effect across gender groups may operate through the MCAT verbal.
- Using a variety of definitions of a peer group in the school-specific fixed effects model, we find no evidence that peer groups affect specialty choices or performance on the board exam for males or blacks.
- The only evidence of a peer effect is for female students. Females who attend schools where the other female students received relatively high scores on the verbal portion of the MCAT exam subsequently receive higher board scores themselves, although the magnitude of this effect is small.
- In all specifications, the effect of the specialty preferences of a students peer group on his own specialty choice disappears after controlling for school fixed effects.
- Identification problem: if we specify the contextual effects, that is the characteristics of
 neighbors in the equation describing the outcome, as the neighborhood averages of the
 individual effects, then we cannot estimate separately the social interactions coefficient from
 the coefficient of the contextual effect.

$$y_i = \frac{\alpha_0}{1 - \beta} + \alpha \mathbf{x}_i + \frac{\beta}{1 - \beta} \alpha \mathbf{x}_{\nu(i)} + \frac{\theta}{1 - \beta} \mathbf{z}_{\nu(i)} + \epsilon_i.$$

- (1- beta) magnifies the residential effect
- Ioannides (2002) "Residential Neighborhood Effects"
- loannides (2002) investigates housing maintenance decisions which allow for social interactions within small residential neighborhoods with data from the American Housing Survey for 1985 and 1989.
- The paper identifies an important, and statistically very significant, effect of social interactions, an owner reacts to maintenance behavior of her neighbors, while individual and dwelling unit characteristics are accounted for.

I specify an empirical model for a homeowner's maintenance decision as a reaction function to her neighbors' housing maintenance decisions, $\Pi_i Y_t$, of own socioeconomic characteristics, z_{ht} , of the dwelling unit value as of the previous period, $v_{i\kappa t-1}$, and of socioeconomic characteristics of neighbors conditional on neighborhood and dwelling unit characteristics, $E[z_{ht}|x_{\kappa t},q_{it}]$:

$$y_{i\kappa ht} = \alpha + \mu y_{i\kappa ht-1} + \beta \prod_i Y_t + \theta v_{i\kappa t-1} + \eta z_{ht} + \gamma E[z_{ht}|x_{\kappa t}, q_{it}] + u_{i\kappa ht},$$

•	That is, the maintenance behavior of individual homeowners is influenced by those of their neighbors. So a public policy interventions that fix up neighborhoods may bring about urban neighborhood change through a social multipliers					

Lecture 5. Basic facts of Graph and Network Theory for Social Network Modeling

Centrality A micro measure that captures the importance of a node's position in the network.

Different measures of centrality

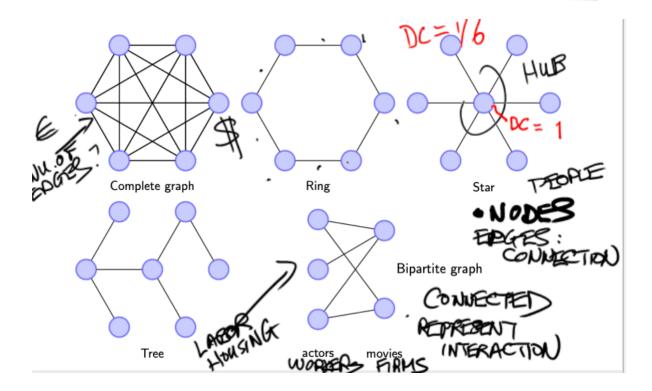
Degree centrality: for node i: $d_i(g)/n - 1$, where $d_i(g)$ is the degree of node i

Closeness centrality: Tracks how close a given node is to any other node: for node i, one such measure is

$$\frac{n-1}{\sum_{j\neq i} \text{graph distance } i \text{ to } j}$$

Betweenness centrality: Captures how well situated a node is in terms of paths that it lies on (see the Florentine marriages example from the previous lecture).

See Easley and Kleinberg, sections 17.1, 17.2, 17.3.



Lecture 6. Autor (2014) & Rossi-Hansberg (2010)

Rossi-Hansberg et al. (2010) (see details below), and the "natural experiment", the rent decontrol in our neighboring Cambridge, MA, discussed in

Autor David H., Christopher J. Palmer, and Parag A. Pathak. 2014. "Housing Market Spillovers: Evidence from the End of Rent Control in Cambridge, Massachusetts." *Journal of Political Economy.* 122(3):661-717. Abstract follows:

These papers rest heavily on housing maintenance decisions in an urban context. In contrast to Ioannides (2002), Rossi-Hansberg et al. work with an spatial equilibrium model. The appendix of Autor et al. also outlines a spatial equilibrium model. That is, the assumption that individuals move so as to equalize utility they derive at all neighborhoods implies a covariation of prices, incomes, and amenities. For more on this, look at Ioannides (2013), section 5.1.1 and 5.1.2.

 Both use a spatial equilibruim model (using experiments) in contrast to loannides (2002) using a structure model

Autor

- Autor et al. measure the capitalization of housing market externalities into residential housing values by studying the unanticipated elimination of stringent rent controls in Cambridge, Massachusetts, in 1995.
- we find that **rent decontrol generated substantial, robust price appreciation at decontrolled units and nearby never-controlled units,** accounting for a quarter of the \$7.8 billion in Cambridge residential property appreciation during this period

Table 3. Effects of Rent Decontrol on Assessed Values
Dependent Variable: Log of Assessed Property Value (1994, 2004)

	(1)	(2)	(3)	(4)
RC	-0.504***	-0.504***	-0.515***	
	(0.075)	(0.052)	(0.052)	
RC x Post	0.217*** (0.039)	0.227*** (0.037)	0.249*** (0.034)	0.221*** (0.040)

• Findings from other large-scale social experiments

The "experiment" in Autor et al. is a "natural one:" The rental housing market was controlled in 1969 and decontrolled in 1995. They don't work with a model, but the model in the appendix is helpful. It was summarized in the lecture.

Utility function: $U \equiv Ac^{1-\alpha}h^{\alpha}$. Individuals sort into neighborhoods, n = 1, ..., N, according to income, y_n . A denotes Amenities, so for neighborhood n are defined as:

$$A_n = \int m_n(\ell) y_n^{\beta}(\ell) d\ell,$$

where ℓ are locations in neighborhood n, and it an aggregation of maintenance spending by income levels. Individuals maximize utility subject to their budget constraint,

$$c + p_n h_n = y_n.$$

So, non-housing and housing consumptions are: $c_n = (1 - \alpha)y_n, p_n h_n = \alpha y_n$. The corresponding maximum utility, the indirect utility function, is,

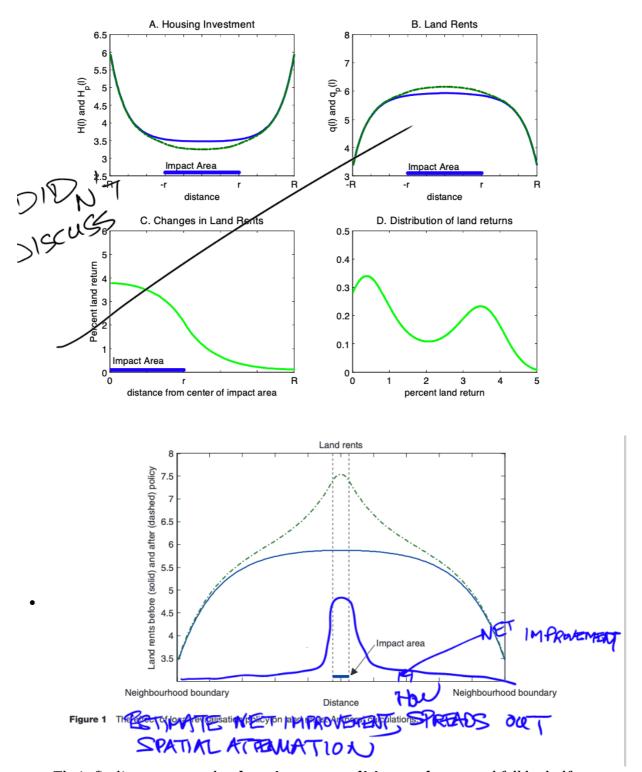
$$V_n = A_n \alpha^* y_n p_n^{-\alpha}$$
, where: $\alpha^* \equiv (1 - \alpha)^{1 - \alpha} \alpha^{\alpha}$.

For spatial equilibrium, individuals must be indifferent as to where they live across all locations ℓ in the neighborhood. That is, utility is equalized to, say, \bar{U}_n . This implies, after taking logs, the following:

$$\ell n p_n = rac{1}{lpha} [\ell n A_n + \ell n y_n - \ell n ar{U}_n + \ell n lpha^*].$$

So, higher incomes, or higher amenity values, on the RHS, are reflected in higher prices, on the LHS, in the above equation. This explains why highly sought after neighborhoods have higher prices or rents.

- Rossi-Hansberg et.al (2010)
- An urban renewal experiment in Richmond, VA, called Neighborhoods in Bloom.
- The study finds that increases in land values decline with distance from the impact areas, as expected: housing externalities decline roughly by half every 1,000 feet.
- Further, the increase in land values arising from externalities brought about by the revitalization range between 2 and 6 dollars per dollar invested.
- In conclusion, as a result of the revitalization program, housing investments fall and land prices rise throughout the neighborhood.
- The lesson learned: there is huge improvement from spending on some properties to other neighboring properties. This is the endogenous social effect. But, there is spatial attenuation, by about one-half per 1000 ft of distance from a property.



• Their findings suggest that **housing externalities are large**, and fall by half approximately every 1,000 feet, and considerably amplify the effects of revitalization programs.

Lecture 7. Reflection problem, identification of social interactions, neighborhood choices

- Neighborhood choice are influenced by many factors
- Datasets:
- Data sets like the American Housing Survey (AHS) allow working with residential neighborhoods, made up of immediate neighbors. The Panel Study of Income Dynamics (PSID) has also been used by economists, but in that data set, neighborhoods are typically broader, defined as census tracts.
- Neighborhood choice help overcome the **reflection problem** since neighborhood choice is a decision and therefore taking into consideration adds information.
- Reflection problem: The problem surfaces when one tries to predict the behavior of an individual by the behavior of the group of which the individual is a member.
- Solving it using heckman selection term E[error | decision = 1/0]

Knowledge of choices allows us to estimate the expectation of ϵ_{Bi} , conditional on having chosen high-income specialty. This conditional expectation is a function of a whole bunch of other variables. So, the board score equation can be estimated correctly:

Board score_i =
$$\beta_0 + X_i\beta_1 + \text{spec. pref.}_i\beta_2 + \overline{MCAT_i}\beta_3 + \overline{\text{spec. pref.}_i}\beta_4$$

+new terms + ϵ'_{Bi} .

The new terms correct for the fact that the expectation of the error for those who specified high-income specialty is not zero. In other words, there is a misspecification if this correction is not carried out.

 Ioannides and Zanella (2008) "Searching for the Best Neighborhood: Mobility and Social Interactions."

Ioannides and Zanella (2008) explore this angle by using PSID data that allow them to follow households over two successive waves of the data, from 2001 to 2003, and to relate residential moves to socioeconomic characteristics $\mathbf{z}_{\nu_o(i)}$ and $\mathbf{z}_{\nu_d(i)}$, respectively of origin and destination neighborhoods defined as census tracts, and own characteristics, \mathbf{z}_i . These authors estimate the propensity to move between those two years by means of linear and nonlinear probability models,

$$Prob_i = \alpha_0 + individual \ effects + \alpha_{o,i} \mathbf{z}_{\nu_o(i)} + \alpha_{d,i} \mathbf{z}_{\nu_d(i)} + \epsilon_i,$$

with a full complement of individual characteristics included. They seek to examine whether $\alpha_{o,i}, \alpha_{d,i}$ vary systematically between households with and without children. For households that do not move, origin and destination tracts coincide.

- For endogeneity of neighborhood characteristics and of prices, using as instruments the average characteristics of neighborhoods surrounding respondents' own
- Ioannides and Zanella also assume that family composition is exogenous with respect to households' unobserved preferences for neighborhoods.

• They find that neighborhood effects in the form of contextual effects do affect significantly, and in the directions predicted, the propensity to move for households with school-age children, but not those without school-age children.

Main findings

- They find that neighborhood effects in the form of contextual effects do affect significant the propensity to move for households with school-age children.
- They find, more specifically, that **mean income and the share of population in the census tract in one's own race-ethnic group who recently moved into that neighborhood both increase the propensity to move in for households with children,** but have no effect on households without children.
- They find no effect of neighborhood education
- The percentage of residents who are foreign- born or on public assistance decrease the propensity to move in for households with children, but exert no such effects for others
- The share of children with poor linguistic skills in a neighborhood encourages leaving it and discourages entering it, for households with children,
- the percentage of residents who recently moved into a neighborhood, a proxy for neighborhood instability, are statistically significant and encourage moving out of a neighborhood and encourages moving into it, for households with children but not those without children, respectively.

Assumptions:

- (1) No cross-neighborhood interactions (all relevant interactions are within the tract)
- (2) Neighborhood observables and unobservable are uncorrelated. (reflection problem arises)

Lecture 8. Neighborhood Effects in the Acquisition and Accumulation of Human Capital. ******

• Kremer's findings on neighborhood effects

Kremer's Findings on Neighborhood Effects

Let $h_{i,t+1}$ denote human capital, measured as educational attainment in years of formal schooling, of a member of the *i*th dynasty in generation t+1, and let h_{it} , $h_{i't}$ denote human capital at t of her parents i, i'; $\nu(i)$ denotes the neighborhood where agents i and i' lived at the time of their offspring's upbringing, with its size being $|\nu(i)|$.

Kremer (1997) postulates the following law of intergenerational transmission of educational attainment, a dynamic version of (??) applied to human capital alone:

$$h_{i,t+1} = a_0 + \frac{\alpha}{2}(h_{it} + h_{i't}) + \frac{\beta}{|\nu(i)|} \sum_{j \in \nu(i)} h_{jt} + \epsilon_{it+1}, \tag{7}$$

and a_0 denotes an exogenous intercept and $\epsilon_{i,t+1}$ a stochastic shock. Kremer uses Equ. (7) to estimate coefficients α and β , and to study the intertemporal evolution of the variance of schooling (which may also be interpreted as a measure of inequality of log earnings). This estimation as well as those by Ioannides, discussed below, are made possible thanks to confidential access to PSID geocodes that allows them to link respondents to the census tracts where they reside. See Chapter 2, Appendix.

- As Kremer says, "living in an educated neighborhood increases the expected education for one's child by three-quarters [much as] as marrying an educated spouse
- Ioannides (2013) reports on two types of empirical applications with richer interaction structures, First come empirics with models that extend Kremer and Borjas and involve parametric and non-parametric estimations using PSID data. Then it reports estimation results that highlight the role of parental involvement. The second type of empirical application, section 6.5.7, shows that households deliberately choose neighborhoods with "good" social interactions.
- Patacchini and Zenou (2011) The role of Parental Involvement
- Intergenerational transmission of human capital

Patacchini and Zenou (2011) take this aspect deeper by exploring the properties of parental input and of the neighborhood effect, interpreted as contributions to socialization that are internal and external to the family, respectively. Their theoretical model is simpler than that of section ?? and leads to sharp predictions. Individuals living in "good" neighborhoods with better educated parents who look after them enjoy higher chances for reaching high educational levels. Living in neighborhoods with "bad" neighborhoods with low-quality schools and unfavorable peer pressure with less educated parents lowers their prospects for reaching higher educational levels. Patacchini and Zenou confirm these predictions empirically.

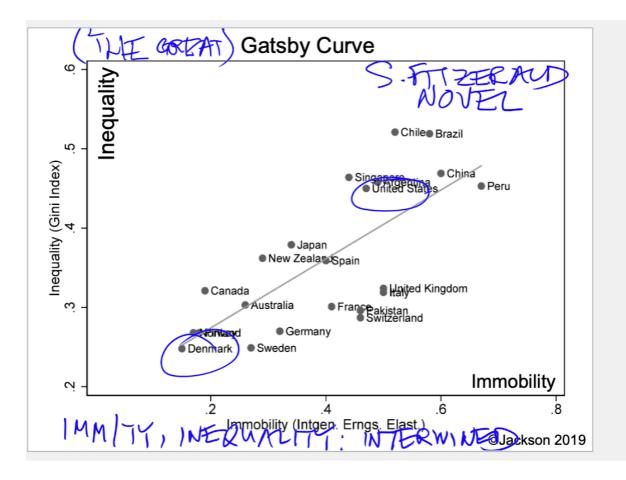
• Council housing (the assignment are uncorrelated to tenant's own education or concern for their children's education)

The authors find evidence of sorting when regressing the mean years of education of parents who recently moved into private dwellings in each ward against the proportion of adults with A-levels residing in that ward.

- they find no such correlation for those who moved into council dwellings
- the authors find that the propensity of highly educated parents, estimated as a probit model, to **read to their children is more sensitive to the percentage of high-skilled population** in the neighborhood than that for low-educated parents.
- Finally, they estimate the probability that individuals attain high education levels as a function of the parents' propensity to read to their children and of the percentage of high-skilled population in their neighborhood of upbringing, with many other controls in- cluded. They find highly significant positive marginal effects, 0.11 and 0.07
- when they estimate the probability that **individuals attain low education level** as a function of their parents' propensity to read to their children and of the percent- age of high-skilled population in their neighborhood of upbringing, again with many other controls also being included, they get highly significant negative
- Thus parental involvement is more important than neighborhood quality for highly educated parents but less important relative to neighborhood effects for low-educated parents.
- Datcher (Tufts)
- Aware that because of correlation between individual characteristics and neighborhood var's, Datcher included additional var's: "If neighborhood coefficients are not affected when these variables are included, it seems likely that the neighborhood characteristics do, in fact, reflect the effects of neighborhood quality.
- This paper addresses the effects of socioeconomic background on education and earnings of black and white men ages 23-32. It examines not only the effects of the socioeconomic status of an individual's parents, but also the effects of characteristics of the individual's community of origin. While other studies have included variables measuring differences due to region and/or size of place of origin, this paper also controls for differences between individuals at the more disaggregated neighborhood level, the zipcode of the residence of the parents, made possible by the author's affiliation at the time.

Lecture 9. Social Networks and Labor Markets (Laura Gee)

- Spatial Aspects of Inequality
- Gatsby Curve



- A simple calculation of unemployment rate, vacancy rate and number of contacts
- U: unemployment rate, V: vacancy rate, S: number of contacts
- (1-U)*V, the probability of getting info about an opening,
- the prob that none of S contact pass info 1-[(1-U)*V]^S
- Prob that at least one of S contact pass info 1-(1-[(1-U)*V]^S))
- S increases, Prob increases; V increases, Prob increases; U increases, Prob decreases

Lecture 10. Laura Gee 'Social Tie' Study using Facebook data (tufts)

- Social network -> better job match?
- Weak/strong tie (shared friends? Subjective report)
- Granovetter (1973)
 90% ties are weak / 90% jobs through a weak tie
 Prob job increases as tie strength increases.
- Structure based ties/Contact based ties
- Causality, unobservable