The Value of Connections: Evidence from the Italian-American Mafia *

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Abstract

Using declassified Federal Bureau of Narcotics records on 800 US Mafia members active in the 1950s and 1960s, and on their connections within the *Cosa Nostra* network, I estimate network effects on gangsters' economic status. Lacking information on criminal proceeds, I measure economic status exploiting detailed information about their place of residence. Housing values are reconstructed using current deflated transactions recorded on Zillow.com.

I deal with the potential reverse causality between the economic status and the gangster's position in the network exploiting exogenous exposure to potential pre-immigration connections. In the absence of pre-immigration data I use the informational content of surnames, called isonomy, to measure the place of origin.

The instrument is valid as long as conditional on the characteristics of the gangsters (including his region of birth) such exposure influences the gangsters' position inside the network but not the preference for specific housing needs. A standard deviation increase in *closeness* centrality increases economic status by about one standard deviation (100 percent).

Keywords: Mafia, Networks, Centrality, Housing Prices, Value of Connections, Crime, Surnames, Isonomy.
JEL classification codes: A14, C21, D23, D85, K42, Z13

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1 Introduction

In January 2011, exactly 50 years after Robert F. Kennedy's first concentrated attack on the American Mafia as the newly appointed attorney general of the United States, nearly 125 people were arrested on federal charges, leading to what federal officials called the "largest mob roundup in FBI history."[1]

Over the last 50 years the Mafia has continued following the same rules, and is still active in many countries, including the United States. According to the FBI,[2] in 2005 there were 651 pending investigations related to the Italian-American mafia; almost 1,500 mobsters were arrested, and 824 were convicted; of the roughly 1,000 "made" members of Italian organized crime groups estimated to be active in the US, 200 were in jail.[3]

Despite the magnitude of these numbers, the illicit nature of organized crime activities has precluded empirical analysis and the literature has overwhelmingly been anecdotal or theoretical (Reuter, 1994, Williams, 2001).[4]

This study uses declassified data on 800 Mafia members who were active just before the 1961 crackdown to study the importance of connections inside such a secret society, linking the network position of mobsters to an economic measure of their success. The records are based on an exact facsimile of the Federal Bureau of Narcotics (FBN) secret files on American Mafia members in 1960 (MAF, 2007).[5]

I deal with the potential incompleteness of the records and non-random sampling of

[1]See The New York Times, January 21, 2011, page A21 of the New York edition.

[2]The source is www.fbi.gov.

[3]The Italian Mafia no longer holds full control of racketeering. With the end of the Cold War and the advent of globalization, "transnational" organized crime organizations are on the rise—mainly the Russian mafia, the African enterprises, the Chinese tongs, South American drug cartels, the Japanese Yakuza, and the, so-called, Balkan Organized Crime groups—and their proceeds, by the most conservative estimates, comprise around 5 percent of the world's gross domestic product (Schneider and Enste, 2000, Wagley, 2006). Williams (2001) discusses how networks within and across these organizations facilitate their fortunes.

[4]Levitt and Venkatesh (2000) use detailed financial activities of a drug-selling street gang to analyze gang behavior. But most gangs do not appear to engage in crimes motivated and organized according to formal-rational criteria (Decker et al., 1998).

[5]See Mastrobuoni and Patacchini (2012) for a description of the data and of the network.

the network into account. In the 1960s the total estimated number of mafia members was around 5,000 (Maas, 1968). Since almost all high-ranking members have a record, the 800 criminal profiles are clearly a potentially nonrepresentative sample of Mafia members. In Section 3 I present a method to take such non-random sampling into account (see also Mastrobuoni and Patacchini, 2012). The idea is the FBN's surveillance of mobsters and mobsters' interactions with other mobsters would slowly uncover the network through a Markov chain. The resulting sampling design resembles what is known as snowball sampling.

Since illicit transactions and criminal proceeds inside the Mafia are unobservable, I use the value of the house or the apartment where such criminals presumably resided (or nearby housing) to measure their economic success. Such value is reconstructed based on the deflated value of the current selling price of their housing based on the internet site Zillow.com. Prices are deflated using the metropolitan statistical areas' average housing values from Gyourko et al. (forthcoming). Given that most mobsters were born from very poor families (see Lupo, 2009), the value of the house where they resided, whether it was owned or rented, is arguably a reasonable measure of their illegal proceeds,[6] though reconstructing the original value is certainly prone to error.[7].

The data contain information collected from FBN agents on the gangsters' closest criminal associates, which I use to reconstruct the criminal network.[8] Connections are thought to be the building blocks of secret societies and of organized crime groups, including the Mafia. According to Joe Valachi's 1963 testimony, the first rule in Mafia's decalogue states that "No one can present himself directly to another of our friends. There

[6]A large literature has shown the link between housing demand and income (see Goodman, 1988).

[7]Any classical measurement error would inflate the standard errors, making the inference more conservative.

[8]In the 1930s and up to the 1950s the FBN, which later merged with the Bureau of Drug Abuse Control to form the Bureau of Narcotics and Dangerous Drugs, was the main authority in the fight against the Mafia (Critchley, 2009). For example, in New York the Federal Bureau of Investigation had just four agents, mainly working in office, assigned to the mafia, while in the same office more than 400 agents were fighting domestic communists (Maas, 1968).

must be a third person to do it" (who knows both affiliates) (Maas, 1968).[9]

As a consequence, gangsters who are on average closer to all the other gangsters need fewer interconnecting associates to expand their network. Such connections are important to reach leadership positions, as in the Mafia these are not simply inherited.[10]

Sparrow (1991) and Coles (2001) propose the use of network analysis to study criminal network. However, apart from some event studies based on a handful of connections, empirical evidence on criminal networks is scarce.[11][12]

There is considerable more robust empirical evidence on the importance of connections in other contexts. Among common criminals researchers have found evidence that criminals' behavior depends on the behavior of their peers (peer effects) (see Baker and Faulkner, 1993, Bayer et al., 2009, Drago and Galbiati, 2012, Haynie, 2001, Patacchini and Zenou, 2008, Sarnecki, 1990, 2001, Sirakaya, 2006).

An old and extensive literature in labor economics documents the importance of friends and relatives in providing job referrals Bayer et al. (2008), Glaeser et al. (1996), Montgomery (1991). Networks have been shown to be important for workers' incentives Bandiera et al. (2009), Mas and Moretti (2009), immigrant welfare recipients (Bertrand et al.,

[9]The remaining 9 rules are: never look at the wives of friends, never be seen with cops, do not go to pubs and clubs, always being available for Cosa Nostra is a duty - even if one's wife is going through labor, appointments must be strictly respected, wives must be treated with respect, only truthful answers must be given when asked for information by another member, money cannot be appropriated if it belongs to others or to other families, certain types of people can't be part of Cosa Nostra (including anyone who has a close relative in the police, anyone with a two-timing relative in the family, anyone who behaves badly and does not posses moral values). The same rules have been found on a piece of paper ("pizzino") that belonged to the Italian Mafia boss Salvatore Lo Piccolo during his 2007 arrest.

[10]Soldiers elect their bosses using secret ballots (Falcone and Padovani, 1991, pg. 101).

[11]Morselli (2003) analyzes connections within a single New York based family (the Gambino family), Krebs (2002) analyzes connections among the September 2001 hijackers' terrorist cells, Natarajan (2000, 2006) analyzes wiretap conversations among drug dealers, and McGloin (2005) analyzes the connections among gang members in Newark (NJ).

[12]There is considerable more theoretical work. Most studies have focused on a market structure view of organized crime, where the Mafia generates monopoly power in legal (for a fee) and illegal markets. Among others, such a view is present in the collection of papers in Fiorentini and Peltzman (1997), and in Reuter (1983), Abadinsky (1990), Gambetta (1996), and Kumar and Skaperdas (2009). Only two theoretical papers have focused on the internal organization of organized crime groups. Garoupa (2007) looks at the optimal size of these organizations, while Baccara and Bar-Isaac (2008) look at the optimal internal structure (cells versus hierarchies).

2000), for retirement decisions (Duflo and Saez, 2003), for aid (Angelucci and De Giorgi, 2009, Bandiera and Rasul, 2006), and for education (Calvó-Armengol et al., 2009, De Giorgi et al., 2010, Patacchini and Zenou, 2012).

In recent years the interest has shifted toward understanding not just peer influence, or the influence of direct links, but how the whole architecture of a network, thus including indirect links, influences behavior and outcomes (Ballester et al., 2006, Goyal, 2007, Jackson, 2008, Vega-Redondo, 2007). Empirical evidence is scarce but growing, with the main burden being the endogeneity of the network (see Blume et al., 2012).

In such non-experimental settings the variation that identifies the effect of networks may be partly driven by homophily (the tendency of individuals to be linked to others with similar characteristics) or unobserved characteristics which determine someone's position in the network, as well as his or her outcomes.

Real networks can hardly be generated entirely through an intervention. Experimental studies on networks typically randomly assign information or other treatments, taken the network as given (Alatas et al., 2012, Fafchamps et al., 2013). Banerjee et al. (2013) go one step further, developing a model of information diffusion through a social network, which they estimate using data on a micro-finance loan program (see also Blume et al., 2012).[13]

Alternatively, one can avoid making any causal claims. Ductor et al. (forthcoming) focus on predictions, and show that researchers' network centralities help to predict future research output.

The final option is to use an instrumental variable strategy. (Munshi, 2003) uses rainfall in the origin-community as an instrument for the size of the network at the destination (the United States). Mexican immigrants with larger networks in the US face better labor conditions.

[13] They also validate the structural estimation using time-series variation they do not use in the estimation.

But connections, their number, as well as their quality, are potentially even more important in a world without enforceable contracts, where secrecy, reputation, and violence prevail. Francisco Costiglia, alias Frank Costello, a Mafia boss who according to the data was connected to 34 gangsters, would say "he is connected" to describe someone's affiliation to the Mafia (Wolf and DiMona, 1974).

This implies that in the underworld such bonds are even more likely to be the outcome of a deliberate choice. Several factors might influence the decision about whether to connect and do business with another gangster. While Ballester et al. (2006, 2010) show that in non-cooperative games with linear-quadratic utilities the activity of individuals is proportional to the *eigenvector* centrality (the "key-player" having the largest *eigenvector* centrality), several assumptions of that model would not hold for the Mafia: conditional on operating inside the same area and being part of the same Mafia "Family," the hierarchy (introducing cooperativeness) as well the expected profits of such connections, are likely to influence the formation of a link; with decisions going from top to bottom, and risk of whistleblowing (absent in Ballester et al. (2006) and Ballester et al. (2010)) being traded off with the expected charge imposed on criminal proceeds. Moreover, connections are likely to depend on complementarities and substitutabilities in criminal (robberies, murders, drug dealings, etc.) as well as non-criminal activities (restaurants, casinos, etc.) of the members.

Instead of modelling such a complex network formation mechanism, I am going to rely on an instrumental variable strategy based on information collected from the pre-immigration community (as in Munshi, 2003). Absent detailed information on the communities of origin for all the members born in the US, I proxy such information with the information on the geographic distribution of the mobsters' surnames in the country of origin (Italy). I develop an individual measure of potential innate interactions with criminal affiliates based on the informational content of surnames, called isonomy, which predicts the gangster's individual number and quality of connections. Given that such measure is based on information collected in the country of origin, Italy, conditional on several individual characteristics of the mobsters (including the region of birth) it should not be correlated with economic status in the country of destination (the United States).[14]

Using the instrument the increase of economic status with respect to a one standard deviation increase in network *closeness* centrality (the inverse of the average network distance from all other gangsters) increases from about 25 percent to about 100 percent, and the p-value on the endogeneity test is close to 10 percent. The results are similar for *eigenvector* centrality, while the results for *degree* (the simple count of connections) and *betweenness* centrality (the bridging capacity across different clusters of the network) tend to be weaker, but for different reasons. While *degree* appears to be a crude measure of someone's importance (the value of connections is increasing in the rank of the gangster), gangsters with high *betweenness* were more likely to be part of the *Commissione*, the governing body of the Mafia. I show that in 1960 bosses with large bridging capacities across network clusters often kept a lower profile by living in more humble housing, which unresolvably biases the results downward.

2 The Origin of American Mafia

Before presenting this empirical study it is important to discuss its historical context. I will talk about when the so-called "made" men came to the United States and how the Mafia operated in the 1960s when the FBN was filing the records I analyze in this study.

Historians define two major waves of immigration from Sicily, before and after World War I (WWI). Before WWI immigrants were mainly driven by economic needs. Several

[14]See Section 4.4 for a thorough discussion about the instrument. Such instrument is also related to the growing literature on trust and family values. Guiso et al. (2006) present an introduction to the importance of culture, defined as "customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation," on economic behavior. The same applies to criminal behavior.

Mafia bosses, like Lucky Luciano, Tommaso Lucchese, Vito Genovese, Frank Costello, etc, were children of these early immigrants. Even though between 1901 and 1913 almost a quarter of Sicily's population departed for America, many of the early immigrant families were not from Sicily. In that period around 2 million Italians, mainly from the south emigrated to the US (Critchley, 2009). These baby immigrants later became street gang members in the slums; they spoke little Italian, and worked side by side with criminals from other ethnicities, mainly Jewish and Irish (Lupo, 2009).

Lured by the criminal successes of the first wave of immigrants, and (paradoxically) facilitated by prohibitionism, the second wave of immigrants that went on to become Mafia bosses were already criminals by the time they entered the United States. Charles Gambino, Joe Profaci, Joe Bonanno, and others were in their 20s and 30s when they first entered the US, and they all came from Sicily.[15] Another reason for this selection of immigrants was the fascist crack-down of the Mafia, which forced some of these criminals to leave Sicily. After the second wave of immigration the Mafia became more closely linked to the Sicilian Mafia and started adopting its code of honor and tradition.[16]

There is no information on when the gangsters, or their families, migrated to the US, the FBN data contain information on their place of birth. About 70 percent of mobsters who were active in 1960 were born in the US, while the rest was split between Sicily (about 20 percent) and the rest of Italy (about 10 percent).

In 1930 and 1931 these new arrivals led to a Mafia war, called the Castellamare war, named after a small city in Sicily where many of the new Mafia bosses came from. The war lasted until Maranzano, who was trying to become the "Boss of the Bosses," was killed, probably by Lucky Luciano who had joined the Masseria Family.[17] This war put Lucky

[15]Bandiera (2003) analyzes the origins of the Sicilian Mafia, highlighting how land fragmentation, absence of rule of law, and predatory behavior generated a demand for private protection. Buonanno et al. (2012) and Dimico et al. (2012) add that at the time of the unification of Italy, the lack of the rule of law and the wealth produced by Sicilian export goods (sulfur mines and lemon trees) contributed to the emergence of the mafia.

[16]See Gosch and Hammer (1975).

[17]Before this event, in order to end the power-struggle between Masseria and Maranzano, Lucky Luciano

Luciano at the top of the Mafia organization but also led to a reaction by the media and the prosecutors.[18] Between 1950 and 1951, the Kefauver Committee, officially the Senate Special Committee to Investigate Crime in Interstate Commerce, had a profound impact on the American public. It was the first committee set up to gain a better understanding of how to fight organized crime, and the main source of information was a list of 800 suspected criminals submitted by FBN's Commissioner Anslinger, most likely an early version of the records used in this paper (McWilliams, 1990, pg. 141).[19]

Throughout the 1950s the FBN continued to investigate the Mafia, and in 1957, an unexpected raid of an American Mafia summit, the "Apalachin meeting," captured considerable media attention. Police detained over 60 underworld bosses from the raid. After that meeting everyone had to agree with the FBN's view that there was one large and well organized Mafia society.[20]

After learning that he had been marked for execution Joe Valachi, who was spending time in jail, became the first and most important informer for the FBN and later for the FBI.[21] Valachi revealed that the *Cosa Nostra* was made of approximately 25 Families. *Cosa Nostra* was governed by a *Commissione* of 7-12 bosses, which also acted as the final

had offered to eliminate Joe "the Boss" Masseria, which he did at an Italian restaurant by poisoning Masseria's food with lead.

[18]In 1936 Thomas E. Dewey, appointed as New York City special prosecutor to crack down on the rackets, managed to obtain Luciano's conviction with charges on multiple counts of forced prostitution. Luciano served only 10 of the 30 to 50 years sentenced. In 1946 thanks to an alleged involvement in the Allied troops' landing in Sicily he was deported to Italy, from where he tried to keep organizing "the organization."

[19]The Committee could not prove the existence of a Mafia and after Luciano's expatriation several other Families headed the organization: Costello, Profaci, Bonanno, and Gambino. Family ties were of utmost importance. According to Bonanno's autobiography (Bonanno, 1983), he became the Boss of the Bosses in part by organizing the marriage between his son Bill and the daughter of Profaci, Rosalia in 1956. In 1957 Gambino took over the leadership.

[20]This meant the beginning of the end of the American Mafia. Robert Kennedy, attorney general of the United States, and J. Edgar Hoover, head of the Federal Bureau of Investigations, joined Harry J. Anslinger, the US Commissioner of Narcotics, in his war against the mob. The same years a permanent Senate Select Committee was formed – the McClellan commission. Anslinger's FBN conducted the investigative work and coordinated nationwide arrests of Apalachin defendants. Lucky Luciano died of a heart attack at the airport of Naples in 1962.

[21]Jacobs and Gouldin (1999) provide a relatively short overview about law enforcement's unprecedented attack on Italian organized crime families following Valachi's hearings.

arbiter on disputes between Families. The remaining 10 to 15 families were smaller and not part of *Cosa Nostra*'s governing body. Each Family was structured in hierarchies with a boss, *Capo Famiglia*, at the top, a second in command, called underboss, *Sottocapo*, a counselor, *Consigliere*, and several capo, *Caporegime*, captains who head a group of soldiers (*regime*) (Maas, 1968).

The FBN data represent a snapshot of what the authorities knew in 1960, thus do not contain information about the Mafia Family each member belongs to. Joe Valachi's testimony confirmed FBN's view (which at the time wasn't FBI's view) that the Mafia had a pyramidal structure with connections leading toward every single member.[22]

3 The FBN Records: a non-random sample of mobsters

The 800 criminal files come from an exact facsimile of a Federal Bureau of Narcotics report of which fifty copies were circulated within the Bureau starting in the 1950s. They come from more than 20 years of investigations, and several successful infiltrations by undercover agents (McWilliams, 1990).

Given that in the US there were an estimated 5,000 members active during those years the list represents a non-random sample of *Cosa Nostra* members. More active and more connected mobsters were certainly more likely to be noticed and tracked, which is probably why most, if not all, big bosses that were alive at the time have a file.

There are no exact records about how the FBN followed mobsters and constructed the network, though with the use of surveillance posts, undercover agents, etc. agents were probably discovering previously unknown mobsters following known ones. Two photographs taken in 1980 and in 1988 show how these discoveries might have looked like

[22] In the data the whole network is connected and the average distance between gangsters is just 3.7.

(Figure 1). This kind of sampling resembles a procedure that is used to sample hidden populations, called snowball sampling (Heckathorn, 1997).

Given an initial distribution of known gangsters p_0 (a $1 \times N$ vector of zeros and ones, called the seed), following such connections for k steps the likelihood of observing a mobsters is

$$p_k = p_0 T^k \ , \tag{1}$$

where T is the transition matrix (columns sum up to one). The stationary distribution p, defined as a vector that does not change under application of the transition matrix, or the likelihood that a mobsters has been observed after several steps, independently of the seed is:[23]

$$p = pT \ . \tag{2}$$

Element p_i of the probability vector p can be interpreted as the likelihood of observing gangster i if one randomly picked the edge of a connection.

The resampling weights are thus going to be the inverse of such probability $w_i^0 = \frac{1}{p_i}$, with $0 < p_i < 1$. Since p_i is almost proportional to the number of connections, such weights are extremely intuitive. Gangsters who have very few connections, and thus are unlikely to be spotted by the FBN are going to receive a large weight, to make up for their being under-represented, and viceversa for gangsters who are highly connected.

The summary statistics Table 1 describes the gangsters with and without correcting for the non-random sampling design.

[23] The Perron-Frobenius theorem ensures that such a vector exists, and that the largest eigenvalue associated with a stochastic matrix is always 1. For a matrix with strictly positive entries, this vector is unique. I approximate p with p_{40}, and compute such distribution multiplying a constant vector of size N (number of nodes) that sums up to one by the 40th power of T.

4 Descriptive Evidence on Economic Status, Network Centrality, and Potential Innate Interactions

A quick look at record number one, Joe Bonanno, (Figure 2) reveals the kind of information that I will use to link someone's network centrality to his economic success. According to the FBN he was born on January 18, 1905 in Castellamare (Sicily), and resided in 1847 East Elm Street in Tucson (Arizona). He had interests in three legal businesses: Grande Cheese Co., Fond du Lac (Wisconsin), Alliance Realty & Insurance (Tucson, Arizona), and Brunswick Laundry Service (Brooklyn, New York), etc.. Finally, his closest criminal associates were Lucky Luciano, Francisco Costiglia (Frank Costello), Giuseppe Profaci, Anthony Corallo, Thomas Lucchese, and Carmine Galante.

I use the value of the house to measure economic success, and information on the associates to reconstruct the network. The instrumental variable is going to rely on the information contained in the gangsters' surnames.

Table 1 shows that only 14 percent of gangsters have no arrest record. Since for these gangsters several variables might be measured with more noise (including the place of residence), in the robustness section the results are going to be replicated without these individuals.

4.1 Housing values and Number of Legal Businesses

There is no database on housing values of 1960 properties, but feeding the exact residence address into Zillow.com produces 641 current real estate values, and for 561 homes (about 90 percent of the sample) there is also information on the year the house was built.[24] The remaining 159 mobsters were not residing in the US anymore (like Lucky Luciano who

[24]One third of the times the exact address did not produce an estimated value, and the nearest house with such information was selected. Since housing values tend to be highly geographically clustered such proxy is likely to reduces the precision of our estimates by a small amount.

had already been expelled from the country), or never lived in the US, and were based in Italy.

Given that the distribution of the year of first arrest has almost full support within the range 1908-1960, one can infer that the data refer to what the authorities knew in 1960.[25] Records do not report any deaths and thus do not include those who were killed before 1960, for example, Albert Anastasia boss of one of the 5 New York City families, the Gambino family.[26] So one needs to reconstruct the value of the house in 1960.

For 608 homes that are in a metropolitan statistical area I use the average housing value in 1960 and 2000 from Gyourko et al. (forthcoming) to deflate the prices, for the remaining 33 homes I use State level data from the Census.[27]

The left Panel of Figure 3 shows the relationship (truncated at the 90th percentile) between the current and the 1960 values. Housing prices have approximately doubled over the last 50 years, though they have increased almost 5 times in San Francisco, while they stayed almost constant in Binghamption, Utica/Rome, or Buffalo. In the New York MSA, where almost 300 gangsters reside prices doubled.

The 1960 5th, 10th, 25th, 50th, 75th, and 90th percentile of the housing value were 39, 50, 95, 190, 325, and 662 thousand dollars. The 95th and 99th percentiles were 1.5 and 4.7 million dollars. The right Panel of Figure 3 shows the housing value density (truncated at the 90th percentile). The mean housing value in 1960 is 400 thousand dollar not weighting the sample, and is smaller (379) when weighting.[28]

I am also going to control for the legitimate earnings opportunities, measured by the number of legal business that gangsters own. Thirty-two percent of gangsters has no businesses, 43 percent has one, 19 percent has two, and the remaining 5 percent has 3, 4, or

[25] Additional evidence is the following description in Michael Russo's file: "Recently (1960) perjured himself before a Grand Jury in an attempt to protect another Mafia member and narcotic trafficker."

[26] His brother Anthony "Tough Tony," instead, was killed in 1963 and is in the records.

[27] See http://www.census.gov/hhes/www/housing/census/historic/values.html.

[28] Table 1 shows that 10 percent of the houses found on Zillow.com were built after 1960. To control for the fact that these houses might have a different valuation I am going to control for a dummy variable equal to one when the houses were built after 1960.

5 businesses. Table 2 shows the list of legal activities that at least 5 percent of members were involved in. Weighting does little to the distribution of legal activities. Most mobsters owned restaurants, drugstores or were otherwise involved with the supply of food. Real estate, casinos, car dealerships, and import-export were also common businesses.

4.2 Network-based Measures of Importance

Each criminal record contains a list of criminal associates. Figure 2 indicates, for example, that Joe Bonanno was associated with Luciano, Costello, Profaci, Corallo, Lucchese, and Galante. There is no evidence about how the FBN established such associations, but each record tends to list the most important (and connected) associates.

Indirected connections are clearly more numerous, as mobsters can be listed as associates in several records. As in Mastrobuoni and Patacchini (2012) I define two mobsters to be connected whenever the FBN lists at least one mobster lists the other mobster in one record. *Outdegree* (the number of associates listed in one file) is bounded by the available space on a record (the maximum is 13), while *indegree* (the number of times someone is listed in other records) is not. For this reason degree (the number of undirected connections) is only weakly correlated with outdegree (37 percent), and mainly depends on *indegree*.[29]

The number of connections is clearly the simplest but crudest way to measure the importance of members. In recent years social network theorists proposed different centrality measures to account for the importance of someone's connections (Borgatti, 2003, Wasserman and Faust, 1994).[30]

Unlike *degree*, which weights every contact equally, the *eigenvector* index weighs contacts according to their centralities.[31] The index takes the whole network into account

[29]In other words, I construct a symmetric adjacency matrix of indirected connections between mobsters' last names. Dealing with changing first names would have been a complex task.

[30]See also Sparrow (1991) for a discussion on centrality indices in criminal networks.

[31]It equals the *eigenvector* of the largest positive eigenvalue of the adjacency matrix, the $N \times N$ 0 and

(direct and indirect connections).[32] The *closeness* index measures the average distance between a node (a member) and all the other nodes, and its inverse is a good measure for how isolated members are. The *betweenness* index measures the number of times a node is on the shortest path between two randomly chosen nodes, measuring member's capacity to act like a bridge between clusters of the network, most likely Families.[33] Since there is no strong theoretical ground to prefer a particular measure, most of the following analyses are going to be based on all four measures of centrality. Though with the Mafia rule that guarantees secrecy–"No one can present himself directly to another of our friends. There must be a third person to do it."– gangsters who are closer to other gangsters need fewer interlinking associates to reach a randomly chosen gangster, while gangsters with important bridging capacities across clusters of the network have more monopoly power in establishing such new links.

Figure 4 demonstrates that the densities of centrality measures are positively skewed. The *eigenvector* index (centrality) has a density that is very similar to that of *degree*, while the density of *closeness* is more symmetrically distributed. The density of *betweenness* has the thickest right tail, meaning that very few mobsters represent bridges between subsets of the network.

Given that the densities of the housing values as well as of the centrality measures have such thick right tails, as in Ductor et al. (forthcoming), all these variables are taken in logs.[34] The corresponding more symmetric densities are plotted in the Online Figure 12.

The centrality measures are positively related to each other (Figure 5). Plotting log *eigenvector* against log *closeness* generates a thick line (ρ =96 percent), which shows that

1 matrix that indicates whether gangster i and j are connected.

[32]As first noted by Granovetter (1973), weak ties (i.e. friends of friends) are important source of information.

[33]The indices have been computed using UCINET 6, and with the exception of *degree* have been normalized dividing each index by its maximum value.

[34]For the *betweenness* centrality index, since 4.5 percent of observations have such index equal to zero, I take the inverse hyperbolic sine transformation $log(y + (y^2 + 1)^{1/2})$.

once one penalizes the larger outliers the two centrality measures are quite similar.

But such large correlation masks a very different variability. The ratio between the standard deviation of the log *eigenvector* index and the log *closeness* index is about 10 to 1. This has to be taken into account when interpreting standardized variations.

The correlations are lower with respect to the other two measures, especially in the lower tail. For *betweenness* it seems to be driven by the fact that several mobsters, despite having many connections, have extremely low levels of *betweenness*. There is some evidence that this is driven by the hierarchies within the mafia. For about 400 mobsters I managed to reconstruct their position within the mafia, though not always referred to their status in 1960. Underbosses and captains (*caporegime*), who would head several soldiers but always within one Mafia "Family," tend to have large *degree*s but low *betweenness*. Counselors and bosses have the largest median *betweenness* measure (about 1/2), while the medians for captains and underbosses are half that large.[35] These differences are considerably lower when using the *closeness* index. Counselors tend to have large *closeness* and *eigenvector* indices, while for bosses the medians of these indices tend to be closer to the medians of captains.

Similarly, "*degree*" seems to be a good measure for centrality when the number of connections is large. When such number is small, the quality of those few connections varies considerably, thus widening the scatter plot.

Weighting the sample the gangsters' average number of connections mobsters drops from 11 to 6, and more generally, the average values of all centrality measures drop when controlling for the non-random nature of the sampling design (Table 1). While the shapes of the distributions stay basically unchanged.

[35] Soldiers have a median *betweenness* index of about 0.18.

4.3 Economic Status, Network Centrality, and Potential Biases

Figure 6 shows that the unconditional expectation of log-housing value, estimated using weighted local polynomial smoothing regression, is increasing in all log-centrality measures, and is not far from being linear. The correlation is stronger when using the *eigenvector* index and the *closeness* index, than when using the simple *degree* or the *betweenness* index (approximately, 20 percent versus 10 percent).

Degree is likely to be a poor measure of centrality when the connections are scarce but valuable. Mobsters with larger *betweenness* indices, instead, might be more likely to keep a low profile, after all they represent the bridge between clusters of the network, most likely Families, and would otherwise put the whole mafia organization in peril (see Baccara and Bar-Isaac, 2008).

For example, Bonanno tells the story about when he decided not to join Lucky Luciano's very lucrative garment industry in New York to avoid being in the spotlights Bonanno (1983). Such bosses might also choose to live in an unpretentious house.

There is indeed evidence of Mafia leaders' preference for unpretentious housing. Defining leaders to be those that the FBN files describe as "leaders" or "bosses," Table 3 shows that such bosses tend to be more central in the network. They tend to have considerably larger *betweenness* centrality than lower-ranked gangster, about 40 percent larger. Other centrality measures differ less between bosses and lower-ranked gangsters. Despite this, bosses tend to live in less expensive housing. This is in part driven by bosses being less likely to be directly involved in narcotics, a very lucrative business. Later we will see that gangsters involved in drug dealing live is houses that are about 30 percent more expensive.

Moreover, the Sicilian origin seems to influence such bias. Recently arrested bosses who were heading the entire Sicilian mafia, Totò Riina and Bernardo Provenzano, were living in very poor houses. Such cautious behavior seems less present in other organized crime groups. A recently arrested boss from the Neapolitan Camorra, Francesco Schiavone, was living in a mansion, built after the house in the Hollywood movie "Scarface." This same pattern between the Italian region of birth and housing values is evident in the data. The distribution of housing value for Sicilian gangsters and peninsular gangsters is quite different (Figure 7). Sicilian-born mobsters tend to live in considerably cheaper housing, especially at the top of the distribution (these differences might also be driven by housing preferences). Since Sicilian origin tends to increase the gangster's centrality, later in Section 5 I will test the robustness of such correlation when controlling for such origin, and well as for additional characteristics of the gangsters. For instance, Mastrobuoni and Patacchini (2012) show that the family composition influences the mobster's centrality, but larger families might also need larger and more expensive housing.

Even controlling for family composition and the number of legal businesses, the gangsters' initial wealth, which is not recorded in the data, might represent an omitted variable. Such wealth might be used to buy both, power inside the mafia and more expensive housing. In the next section I devise a presumably exogenous instrument that is based on the joint spatial distribution of the gangsters' surnames in Italy, which I will show is moderately correlated with network centrality.

4.4 Birthplace and Potential Innate Interactions

Keeping in mind that the mafia leaders' preference to stay in the shadow complicates the relationship between centrality and their economic status, next I present the instrument variable strategy used to isolate the causal effect of gangsters' network centrality on their housing values.

Several authors have highlighted the importance of familial, interpersonal, and communal relationships in determining criminals' success inside organized crime groups (see, among others, Coles, 2001, Falcone and Padovani, 1991, Ianni and Reuss-Ianni, 1972). Though most of such relationships are also likely to influence housing decisions, and thus would lead to implausible exclusion restrictions. For example, larger families might be more powerful, but need also larger housing. Marrying a gangster's daughter is likely to boost someone's power inside the mafia, but might also change someone's housing budget directly.

Ideally, one would use mobsters' innate characteristics, which might influence his future chances to build connections, but are unrelated to his housing choice (other than through the derived centrality in the network). Proximity to other mobsters represents a natural choice. But such proximity should not be related to inherited wealth, as such wealth might as well be used to acquire centrality. Moreover, geographic proximity based on the place of US residence is likely to be endogenous with respect to network centrality: more powerful mobsters might decide to live in the middle of their sphere of influence.

For these reasons I use a measure of proximity that is based on Italian and not US residencies. Why would a measure of residency in Italy matter? Some of the mobsters were born in Italy, but even the second generation Italian immigrants at times kept strong links with the Italian communities their parents had left years earlier. About a quarter of mobsters were born in Sicily, 2/3 were born outside of Italy (mostly in the US) and the rest in other regions of Italy. Properly weighting the data, these fractions are 2/10, 7/10, and 1/10, indicating that Sicilians tend to have more connections.

All but a handful of mobsters were of Italian origin as this was a prerequisite to become a member.[36] Table 1 shows that the average age is 48 years, which means that the average year of birth is 1912, right in the middle of the Italian migration wave. Most mobsters are either first or second generation immigrants.[37]

[36] The few non-Italian gangsters in the data were either French gangsters from Marseille or Corsica, or part of the, so-called, Jewish Mafia.

[37] As for the remaining variables in Table 1, 80 percent of members are married (76 percent when weighting), but only 66 percent of these have children. The overall average number of children is 1 and is about 2 among members with children. 19 percent of members are married to someone who shares her maiden name with some other member (*Connected wife*), though fewer are when weighting (15 percent when the Markov chain weights are used). These marriages are presumably endogamous within the Mafia. Observe that I'm understating the percentage of marriages within the Mafia as some Mafia surnames might be missing in the data. While it is also possible that some women might have a Mafia

While I do not have pre-immigration information on the exact place of origin in Italy, for at least 30 years researchers in human biology have been exploiting the analogy between patrilineal surname transmission and the characterization of families and communities (Lasker, 1977).

For a number of reasons, geographic, historical, as well as social, surnames tend to be highly geographically clustered, particularly in countries with low internal mobility like Italy (see Allesina, 2011, Barrai et al., 1999, Zei et al., 1993).[38]. The geographic distribution of surnames, called isonomy, contains a strong signal about someone's origin. For example, most "Mastrobuoni" are located in the Basilicata region, which is were my father is from.[39] The Bonanno surname is more widespread across the whole country, though, again, most Bonanno families live in Sicily, and a non-negligible fraction lives in Castellamare del Golfo, which is where Joseph Bonanno was born.[40]

Given that i) 30 percent of gangsters were born in Italy and later moved to the US and even those who were born in the US were likely to keep links with Italy, and ii) surnames tend to be geographically clustered, the way the current distribution of a given surname overlaps with the distribution of all the other surnames represents a possible way, possibly the only way, to measure the innate connections stemming from the gangsters' origin country (thus unrelated to US housing prices). The main un-testable identification assumption is that such interaction at the origin does not shape the gangsters' housing preferences, at least not conditional on the region of birth.

surname without being linked to any Mafia family, this is very unlikely conditional on being married to a Mafia associate. The FBN reports an average of 2 siblings per member, while the average number of recorded members that share the same surname is 1.58. Mobsters' criminal career starts early. They are on average 23 years old when they end up in jail for the first time. I do not know the total number of crimes committed by the mobsters but I know in how many different types of crime they have apparently been involved. This number varies between 0 and 9 and the average is about 2.5. Finally, about 60 percent are involved in drug dealing.

[38]See Colantonio et al. (2003) for an overview on recent developments on the use of surnames in human population biology.

[39]One can try out surnames of Italian economists on the following Web sites: http://www.gens.info/ or http://www.paginebianche.it/.

[40]Guglielmino et al. (1991) show that in Sicily genetic *and* cultural transmission are revealed by surnames.

Looking at Figure 8 helps explaining how I construct the index. It shows the current distribution at the zip code level of the members' surnames, according to Italy's phone directory.[41] [42] There are 4,748 zip codes for about 60 million Italians, thus each zip code covers a little more than 12,000 Italians, and an area of about 23 square miles, a reasonable area within which most relationships are likely to get established. In Figure 8 each circle is proportional to the number of surnames present within each zip code. Not surprisingly many surnames show up in Sicily, in Naples, and in Calabria. Many of these surnames appear also in large cities that were subject to immigratory flows from the south, like Milan, Rome, and Turin. Such migration patterns introduce some noise in the instrument, which is why later I also compute a *Potential Innate Interactions* measure that is just based on Southern regions (Campania, Molise, Calabria, Basilicata, Sicilia, Sardegna, Puglia), with Northern regions acting as imperfect placebos, as migration might depend on ethnic networks.

For each members' surname I compute the probability that he shares a randomly chosen zip code located in Italy (as a robustness check I also limit the attention to the South) with other surnames from the list. To be more precise, the index for member i is equal to 1,000,000 times the sum across zip codes j of the fraction of surnames of member i present in zip codes j times the fraction of surnames of the other members ($-i$) in the same zip code:

$$\text{Potential innate interactions index}_i = 10^9 \sum_j \frac{\#surname_{i,j}}{\sum_j \#surname_{i,j}} \frac{\#surname_{-i,j}}{\sum_j \#surname_{-i,j}}. \quad (3)$$

The Potential innate interactions index (in short, interaction index) tends to be small when the fraction of surnames i overlaps little with the fraction of all other surnames

[41] Only four mobsters were neither born in Italy nor in the US. For two of these mobsters (Lansky and Genese the Potential Innate Interactions index is zero).

[42] Ideally one would use the distribution of surnames in 1960, though previous research has shown how persistent such distribution is (Colantonio et al., 2003).

$-i$. Dividing by the the total number of surnames i and $-i$ takes into account that some surnames are more frequent than others.

I can computed such index for all surnames in the data, while information about the Italian community of origin would only be available for those born there. The average index is equal to 36 per one million, though taking the sampling into account it drops to 26, already indicating that more connected mobsters have more interactions (see Table 1). About ten percent of the times the index is zero, either because the zip codes do not overlap or because the surname is not in the phone directory.[43]

Figure 9 shows that the distribution of the interaction index. Mobsters born in Italy tend to have more innate potential interactions than those born outside of Italy (Figure 10). Most mobsters with very large interactions were born in the Western part of Sicily (the 10 cities of birth corresponding to the largest interaction indices are in major US cities (Chicago, NYC, St. Luis), but also Palermo (Sicily), Cerda (Sicily), Trapani (Sicily), Amantea (Calabria). Most of these are well-known mafia enclaves.

When measuring the interactions focussing on Southern zip codes the shape of the bars is very similar, while when focussing on Northern zip codes (the imperfect placebo) the interaction probabilities are considerably lower, and are lowest for Sicilians, which is consistent with the index capturing interactions in the place of origin.

That these interactions influence the centrality measures can be seen in Figure 11 and Table 4. Correlations are between 15 (*eigenvector*, *closeness*, and *degree*) and 30 percent (*betweenness*), indicating that such initial interactions are important, though neither necessary, nor sufficient, to reach the top positions in the organization (those positions that generate bridges across Families). Moreover, the correlation is larger when restricting the interactions to Southern Italy and considerably weaker when restricting the interactions to Northern Italy.

[43]In the regressions I allow the zeros to have an independent effect. Moreover, ideally one would us the mother's surname as well, though such information is not always available.

Regressions in the next Section are going to assign confidence intervals to these relationships, and are going to test their robustness when further controls are added to the model.

5 Regression Results

5.1 Evidence based on Ordinary Least Squares regressions

Starting with simple OLS regressions and with the *closeness* centrality measure, Table 5 shows that doubling the centrality increases the housing value by about 200 percent.[44] Such large elasticities are driven by a very compressed distribution of *closeness* centrality. In terms of a standard deviation increase in log *closeness* (0.12), the increase in housing value is equal to 1/4.

The first column controls only for variables collected from Zillow.com, in particular whether the housing has been built after 1960 (the year of the FBN records) and whether such information is available. The negative coefficient on this variable is capturing that for more expensive housing Zillow.com is more likely to collect information on the year the house was built. Controlling for additional variables (column 2) increases somehow the effect, while adding US State of residence fixed effects reduces them (column 3), partly because the more influential mobsters resided in New York and New Jersey (where housing prices tend to be high).[45] Given that the State of residence measures part of the centrality of mobsters in the remainder of the study I will not control for it, though I should add that

[44] Given that there is one large network, the residuals might be correlated across mobsters. Assuming that such correlation depends on the shortest distance between pairs of gangsters the variance of the residual of gangster i is going to be a function of the sum of all such distances d_{ij} over j. In particular, $\sigma_i = \sum_j \sigma_{ij}(d_{ij})$. Approximating such variance with either a linear function or an exponential function in average distances (the inverse of closeness) one always rejects that distance influences the squared residuals, and thus the correlations across mobsters (see appendix Table 9). Nevertheless, in all regressions the standard errors are clustered at the surname level, which is the level at which the centrality measures are calculated.

[45] Measurement error might also be co-responsible for such drop.

the instrument that is going to be used later in Section 5.2 is, by construction, unrelated to the State of residence (other than through connections).

The last two columns show that similar results are found when using *closeness* in levels rather than in logs, though in such case the predictive power of centrality drops slightly. As for the log, a standard deviation increase in *closeness* centrality (8.27) increases housing values by about a quarter.

Before showing the results for other centrality measures, let me briefly discuss the coefficients on the other regressors. Gangsters born in Italy, in particular those born in Sicily tend to live in cheaper housing, which might either be due to housing preferences or to a more pronounced avoidance to attract attention (though the effects are not significantly different from 0).[46]

Age at first arrest, which might represent a (negative) measure of career experience within the organization tends to be negatively related to housing values, meaning that earlier arrests tend to be related to increased housing values. Not just experience, but also being involved with drug dealing seems to be related to higher housing values, though the coefficient stops being significant once state of residence effects are added to the regression (indicating that the drug dealing business used to be geographically clustered). The number of legal businesses tend to be positively associated with housing values, which is not surprising.

Going to back to the centrality measures, in Table 6 I substitute *closeness* centrality with the other measures, with and without controlling for additional regressors. A quick look at the R-squared reveals that *closeness* centrality is the strongest predictor of housing value. This is coherent with the first rule of the Mafia, which states that only interlinking affiliates, for example B in a network A-B-C, have the power to introduce a direct link between A and B. Mobsters who are on average closer to all other mobsters will thus need

[46]Appendix Table 10 shows that the place of birth, while influencing the housing value, does not introduce heterogeneity in the effect of centrality.

fewer interlinking associates to establish new connections.

In the absence of a network formation theory for such an illegal and secret organization, I will emphasize the results based on the centrality with the highest predictive power, namely *closeness* centrality.

Eigenvector centrality has similar predictive power, which is not surprising given how strongly correlated the two measures are.[47]

The elasticity is larger for *closeness* centrality only because its variation is about 10 times smaller than the one of *eigenvector* centrality. One standard deviation increase in log-*closeness* centrality has about the same impact on housing value as a one standard deviation increase in log *eigenvector* centrality.

The coefficient on *degree*, instead, has relatively larger standard errors, and a standard deviation increase in log *degree* increases housing value by about 11 percent; but, in line with what emerged in Figure 6, the flattest relationship is the one between log housing value and log *betweenness* centrality. Statistically speaking, the slope is 0.

Given that innate interactions have their strongest influence on such centrality, this is quite unfortunate. Especially because, as argued before, such bias cannot be eliminated. All the regressions use the weighting strategy developed earlier on, but the results based on unweighted regressions can be seen in the Online Table 11. The next Section will show this more formally, and will also show whether the instrument is strong enough to be used for the other centrality measures.

5.2 Evidence based on Instrumental Variable regressions

As previously discussed, for a number of reasons ordinary least squared coefficients on centrality measures might be biased. Figure 11 showed that potential innate interactions influence the gangsters' network centrality. Table 7 presents the first stage and second

[47]This indicates that the underlying network formation model might not be far from those that have already been developed (Ballester et al., 2006).

stage regressions in a compact form, focussing on the instruments and on the endogenous variable, while appendix Tables 12 and 13 show all the coefficients.

Having no potential innate connections is allowed to have its own influence on centrality. All centrality measures are positively correlated with the potential, but the coefficient is significant only for *closeness* and *betweenness* centralities.

The instrument is rather weak. In particular, for *closeness* and *betweenness* centrality the F-statistic for the excluded instruments is around 2 when considering the joint significance of interactions and zero interactions (otherwise it is close to 4). While there are no Montecarlo simulations to determine the bias for clustered standard errors, we should take into account that the estimates are likely to be biased toward OLS. Later I will try to increase the strength of the instrument by i) focussing on the 86 percent of gangsters how have been arrested at least once, and for whom all variable are more likely to be measured with precision, and ii) using a measure of interactions based on just Southern Italy, which has been shown is more strongly related to centrality. This is probably because over the last 50 years in the South, particulary when compared to the North, intranational immigration figures have been small.

Instrumenting the centrality measures the coefficients on *closeness*, *eigenvector*, as well as on *degree* centrality tend to be almost 4 times as large as the OLS equivalents, meaning that a standard deviation increase in either *closeness* or *eigenvector* centrality doubles the housing value. As in the OLS case, *betweenness* does not appear to be significantly different from 0, confirming that the gangsters with large bridging capacity tend to keep a lower profile, no matter whether the centrality has been reached exploiting potential innate connections or not.

But overall the relative precision of the estimates tends to be smaller than for the OLS regressions, which is in part due to the instrument's weakness. Indeed, the standard errors are so large that endogeneity is generally rejected (although at p-values that are not too far from 10 percent).

Table 8 performs several robustness checks, and two are aimed at increasing the strength of the instrument. In columns 1 and 2 I restrict the analysis to gangsters who have at least one arrest record. About 85 percent of gangsters have an arrest record, and for these gangsters all the collected information, in particular, the surname, the place of residence, as well as the connections are more likely to be measured with increased accuracy (though the sample is a more selected one).

In particular, surnames, which represent the core information for the instrumental variable strategy, are not easily measured inside the Mafia. Gangsters are typically known by their nickname. Some of the aliases for gangsters mentioned before were: Don Vitone, The Old Man (Vito Genovese); Francisco Castiglia, Frank Costello, Frank Saverio, Saveria (Francisco Costiglia); Joe Bananas, Joe Bononno, Joe Bonnano, Joe Bouventre (Joseph Bonanno), Joe Proface (Giuseppe Profaci); Carlo Gambrino, Carlo Gambrieno, Don Carlo (Carlo Gambino). Knowing the exact name is clearly important to reconstruct its geographical distribution in Italy, and for arrested gangsters such information is clearly more precise.

The OLS coefficient and IV coefficients in columns 1 and 2 are indeed slightly larger, and, based on the Kleibergen-Paap rk Wald F statistic, the instrument becomes more than twice as powerful.

Column 5, where only the distribution in Southern Italian zip codes are used to measure interactions has a similar influence on the Kleibergen-Paap rk Wald F statistic, indicating that migration patterns to the major cities in Central and Northern Italy might have introduced some noise in the instrument.[48]

Columns 3 and 4 test the robustness of the results when getting rid of the zero interaction dummy (thus assuming continuity and linearity at 0), and when allowing the

[48]The same conclusions can be drawn looking at the reduced form regressions, shown in appendix Table 14.

instrument to have non-linear effects on log *closeness*. None of these changes alters the results. Finally, in the last column I add a variable that is clearly endogenous, whether the mobster is married to a "connected" wife, meaning a wife whose maiden name is also the surname of another mobster in the data.

These marriages tended to be arranged for strategic reasons, and would allow gangsters to gain additional power (connections) as well as wealth. Adding this variable increases the OLS estimates while keeping the 2SLS estimate almost unchanged, suggesting that omitted variables (which the instrument takes care of) are indeed biasing the OLS estimate toward zero.[49]

6 Concluding remarks

This paper estimates how in 1960 inside the Italian-American Mafia network centrality influenced economic prosperity, measured based on reconstructed housing values, dealing with the non-random sampling design of such law-enforcement data. .

In the overground world connections, and their whole geometry, have been shown to be related to a variety of economic outcomes. In the underground world such connections are presumably even more important, and yet evidence of this is mainly based on ethnographic studies.

Moreover, even in the overground world researchers have rarely gone beyond just documenting correlations, as networks tend to emerge endogenously out of complicated bilateral and multilateral decision processes. Social scientists have been able to exploit the geometry of the network to develop identification strategies for direct connections (peer effects), but not yet for measures of how central an individual is inside the network. Alternatively, one has to either i) use a two-step estimation procedure where the first step models the endogenous network formation (which is easily prone to model mis-

[49]The potential endogeneity of such marriage hinders stronger statements.

specification), or use an instrumental variable approach.

But instrument for networks with reasonable exclusion restrictions are in short supply. Any characteristic that determines someone's position inside his/her network is also likely to directly influence a multitude of other outcomes. In the Mafia, for example, family relationships, wealth, place of birth, etc. might help securing a centrality in the network, but could easily be related to the demand for housing.

For migrants with strong ethnic identities, instruments naturally evolve from shocks that happen in the country of origin and are thus less likely to influence economic outcomes in the country of destination. Munshi (2003) uses rainfall in Mexico to instrument for the network size of Mexican immigrants to study how such size influences labor market outcomes. Similarly, this paper instruments individual centrality measures using the potential exposure to connections in the gangster's place of origin. In the absence of pre-immigration data I use the informational content of surnames, called isonomy, to measure such place.

On the one hand, mobsters who were on average closer to their peers, and who had more connections and more connections to more connected peers tend to live in more expensive housing. This is consistent with the importance of interconnection capacity in a secret society where unconnected mobsters need a common connection to generate a direct link.

On the other hand, mobsters who act as bridges across clusters of the larger network (given what is know about the Mafia these could be called Mafia Families, or "Mandamenti") tend to keep a lower profile, preferring less expensive housing. The evidence suggests that these tend to be the more important bosses, those who most likely form the governing body of the Mafia (la *Commissione*). In line with Bonnano's autobiography such bosses were less likely to be directly involved in the narcotics businesses, which might be part of the same attention avoidance strategy (Bonanno, 1983).

Despite having to use i) the informational content of surnames to measures the gangsters' roots, ii) today's housing values to reconstruct the 1960 housing values, iii) a subsample of the entire network, the instrumental evidence suggests that a one-standard deviation increase in *closeness* centrality doubles the gangster's housing value. Given that such effects appear to be bound to be close to zero for extremely central gangsters (the information hubs, or bridges) the effects on true economic outcomes, which might not be simply measured with classical errors (wealth in the hands of figureheads might be increasing in centrality) are likely to be even larger.

Finally, while data restrictions prevent researchers from performing similar analyses based on more recent organized crime networks, this might hopefully change in the near future. Understanding how central figures grow up inside criminal networks is fundamental to the design of targeted law enforcement strategies.

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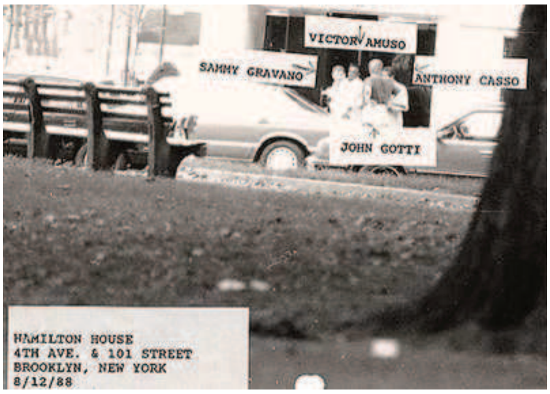
Figure 1: Surveillance pictures of Nick Giso in 1980, and Sammy Gravano in 1988



NAME : Joseph BONANNO

ALIASES : Joe Bananas, Joe Bononno, Joe Bonnano, Joe Bouventre

DESCRIPTION : Born 1-18-1905 Castellammare, Sicily, 5'9", 190 lbs, brown eyes, brown-grey hair, naturalized 5-17-45, Brooklyn, NY.

LOCALITIES FREQUENTED : Resides 1847 East Elm Street, Tucson, Arizona. Travels extensively about U.S. & makes frequent trips to Italy.

FAMILY BACKGROUND : Married Filippa LaBruzzo; daughter: Catherine; sons: Salvatore (married to Rosalie Profaci, niece of Giuseppe Profaci) and Joseph: father: Salvatore; mother: Catherine Bouventre; both parents deceased.

CRIMINAL ASSOCIATES : Lucky Luciano, Francisco Costiglia, Giuseppe Profaci, Anthony Corallo, Thomas Lucchese, Carmine Galante.

CRIMINAL HISTORY : FBI #2534540 NYCPD #B-85172 I&NS #C-6602167 Record dating from 1930 includes arrests for grand larceny, possession of gun, transportation of machine guns, obstruction of justice.

BUSINESS : Has interests in Grande Cheese Co., Fond du Lac, Wis.; Alliance Realty & Insurance, Tucson, Arizona; and Brunswick Laundry Service, Brooklyn, N.Y.

MODUS OPERANDI : Attended 1957 Apalachin Mafia meeting and Binghamton, NY, meeting 1956. One of the most important Mafia leaders in U.S. and attends all top-level Mafia meetings. Makes trips to Italy to confer with Mafia leaders there and to negotiate for international narcotic trafficking.

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Figure 2: Record Number One: Joe Bonanno

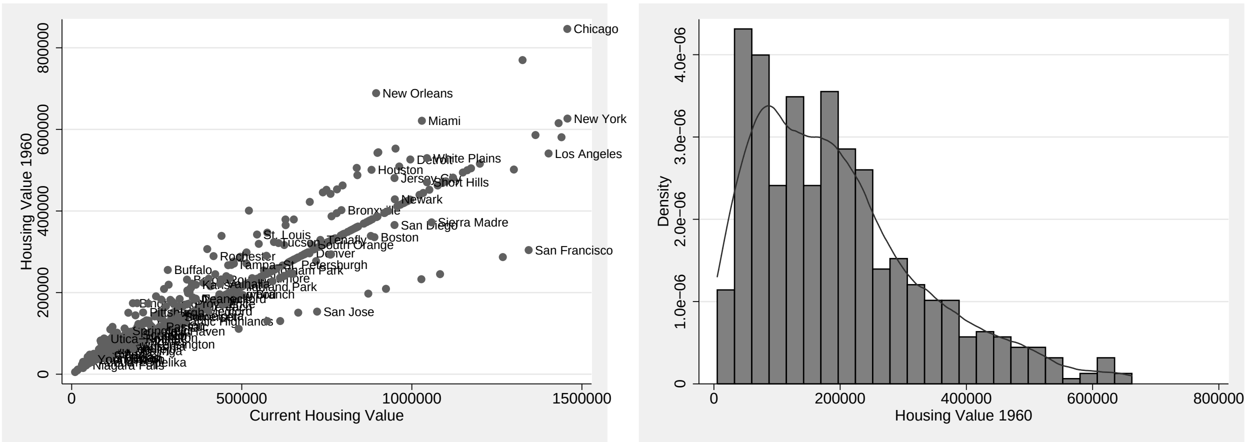

Figure 3: Housing Value Deflators and Distribution

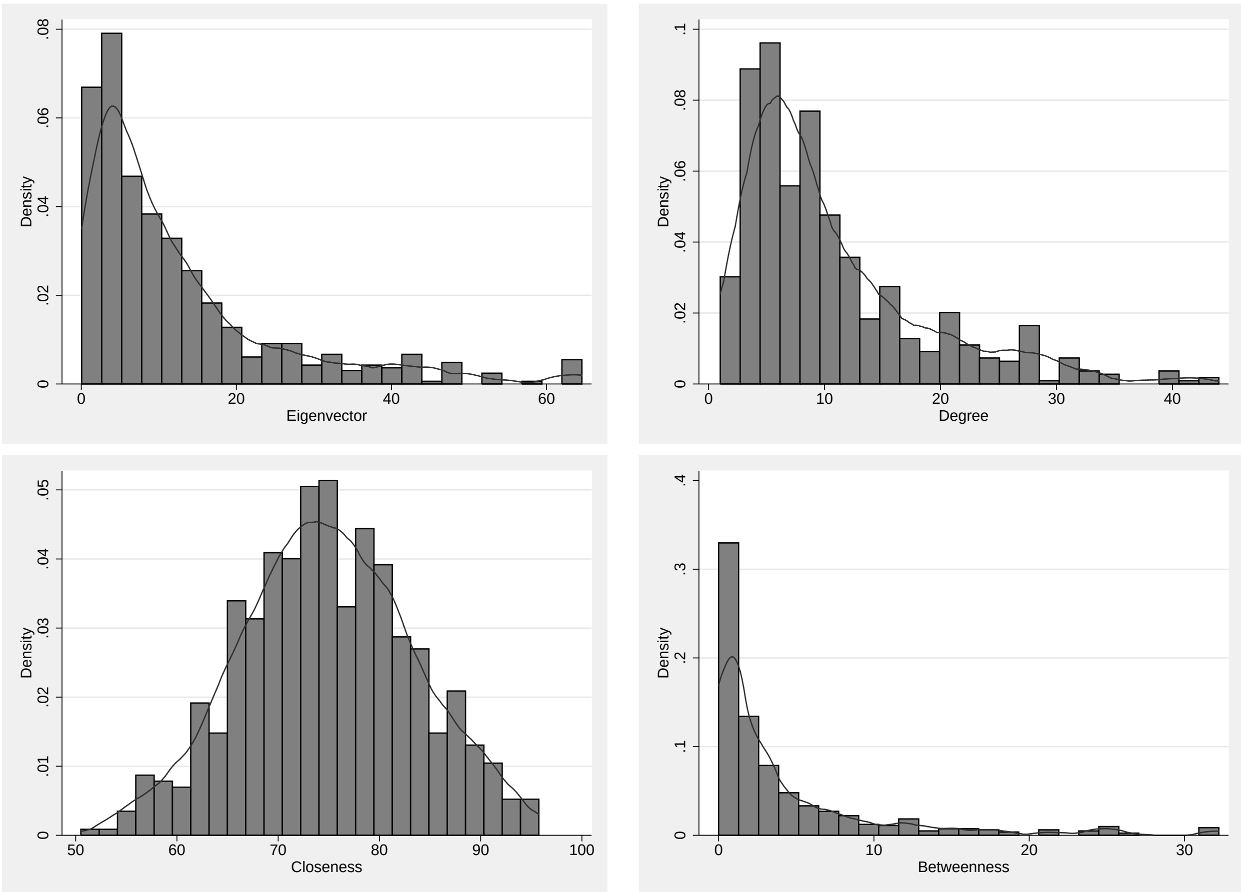

Figure 4: Densities of Centrality Indices

Notes: The density shown excludes the top 1 percent of the distribution.

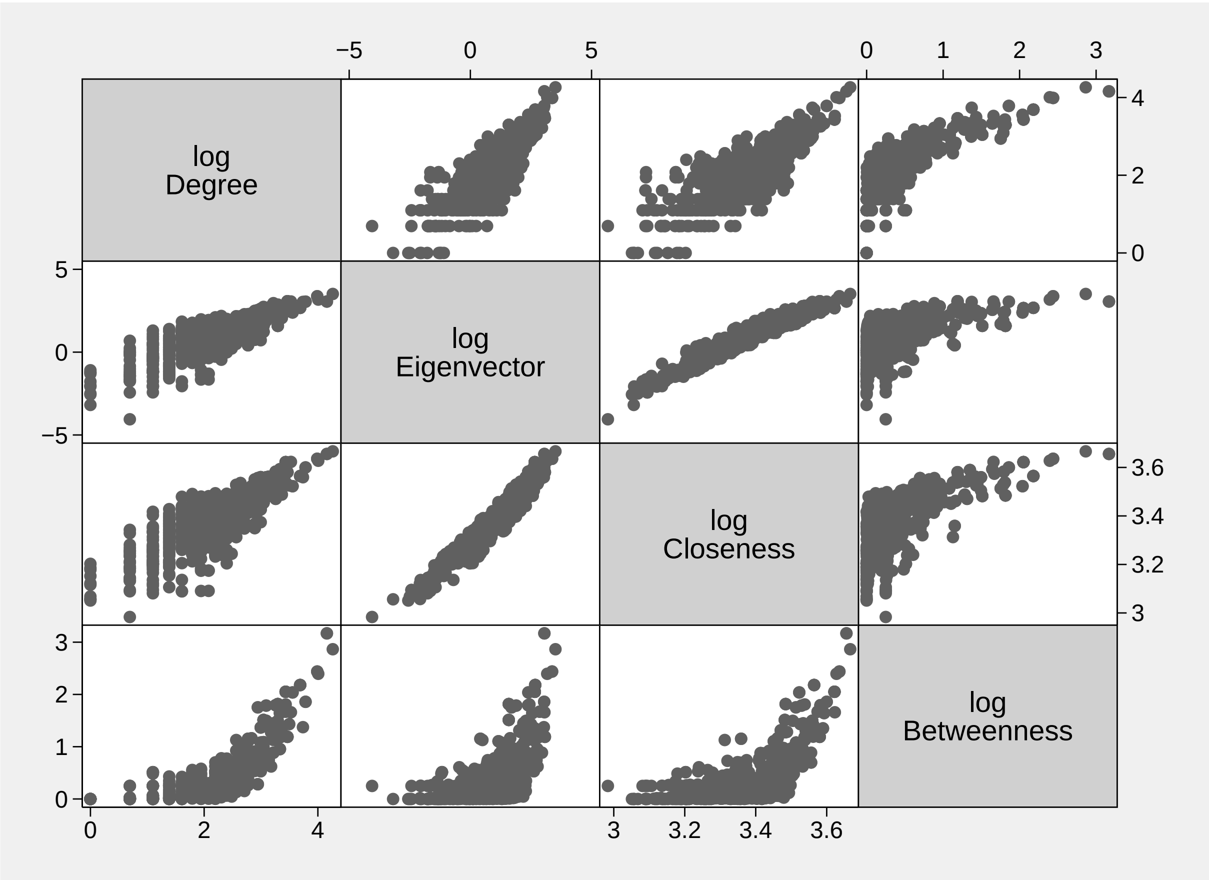

Figure 5: Relationship Between Log-centrality Indices

Notes: The density shown excludes the top 1 percent of the distribution.

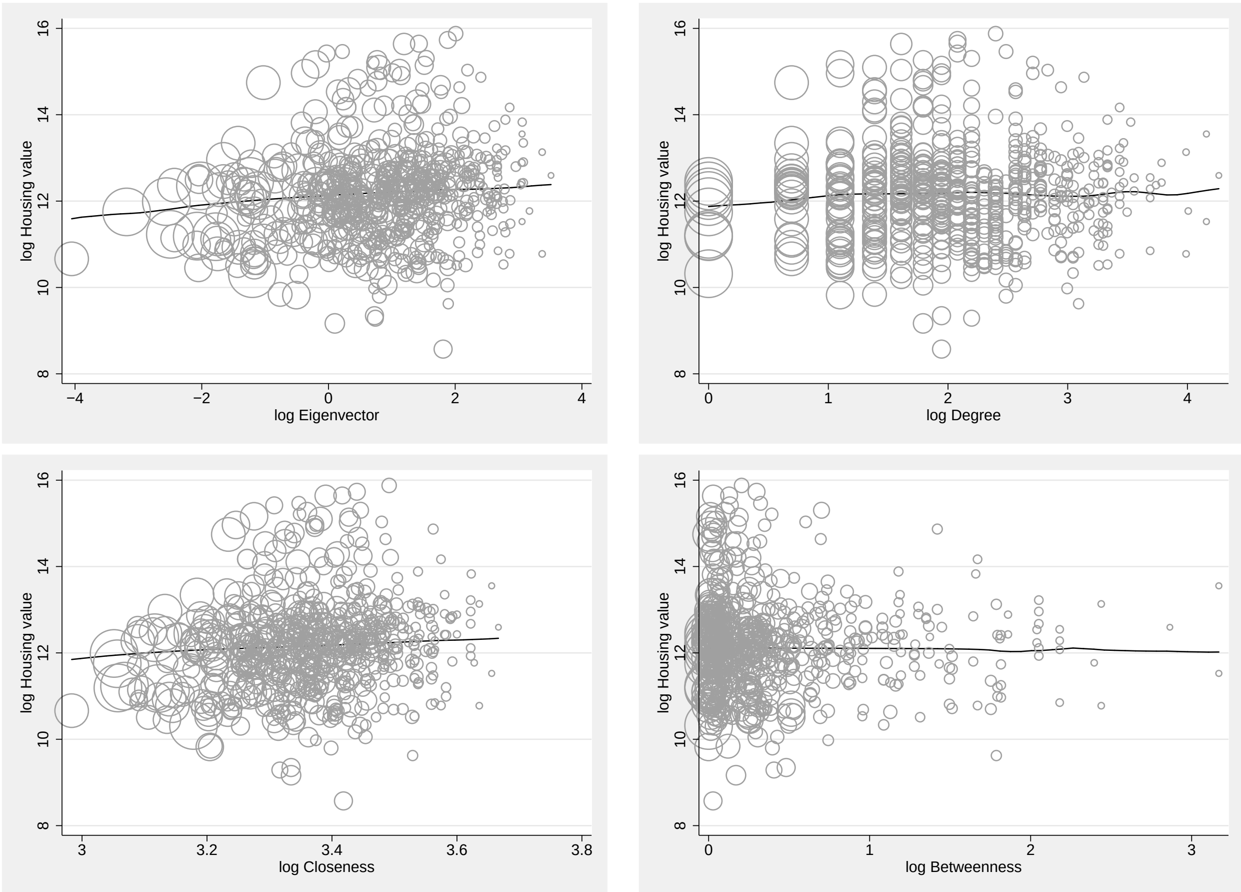

Figure 6: Housing values and Network Centrality (in logs)

Notes: The size of the circles is proportional to the sampling weight. The solid line corresponds to the local polynomial smoothing regression line (using the Epanechnikov kernel).

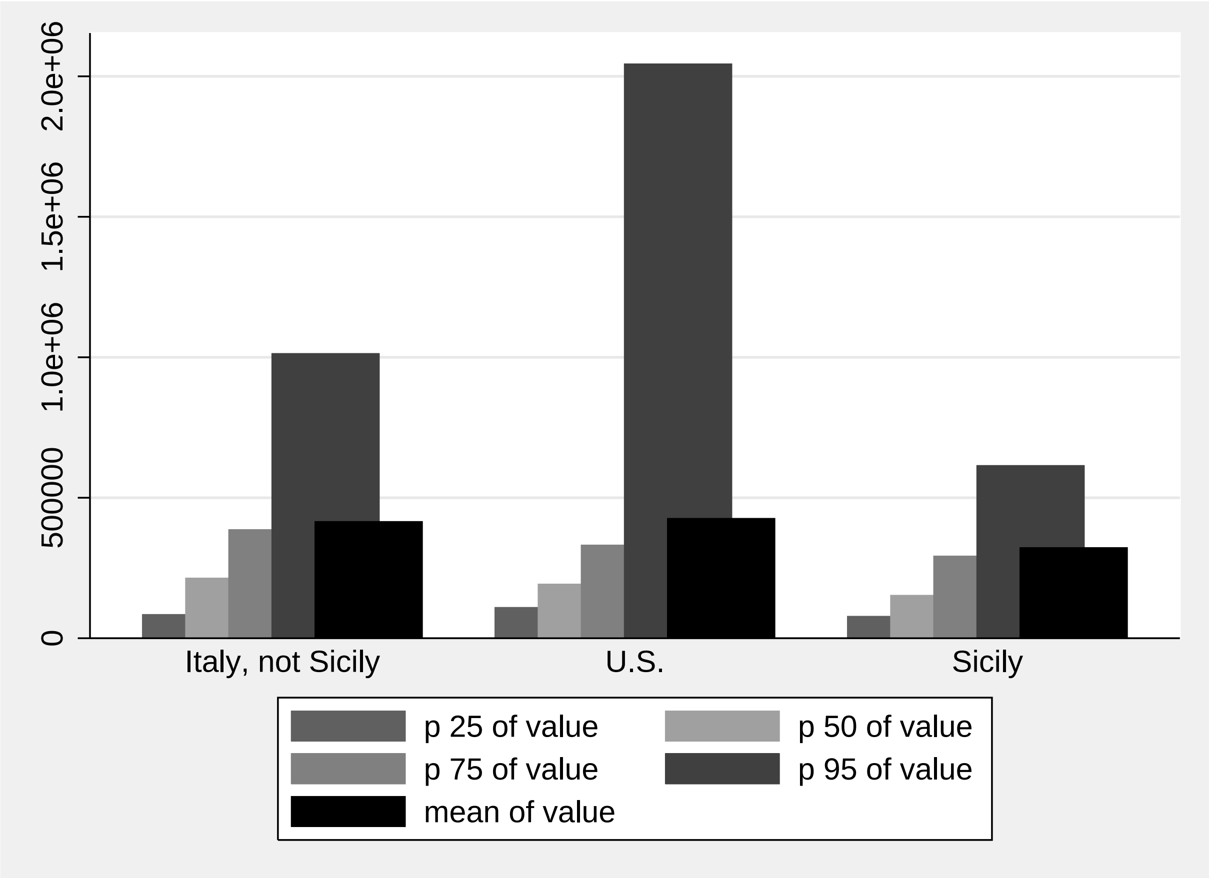

Figure 7: Distribution of Housing Values by Region of Birth

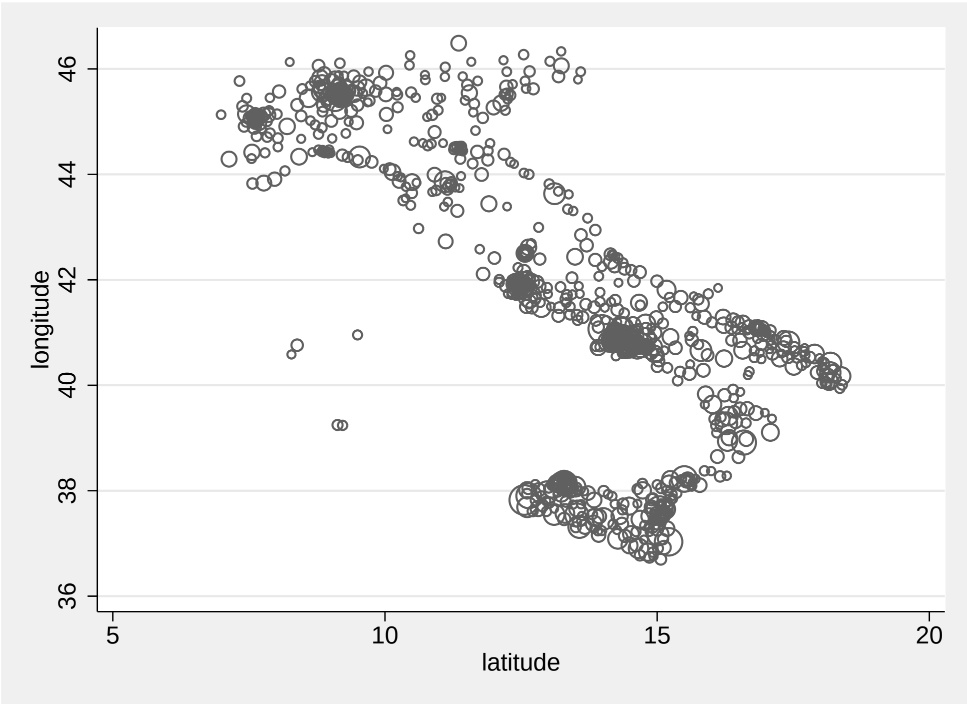

Figure 8: Geographical Distribution of Mafia Surnames.

Notes: Each circle represents a zip code. The size of the circles is proportional to the number of US Mafia members' surnames found in today's Italian phone directory. The plot shows only 20 percent of the distribution of surnames.

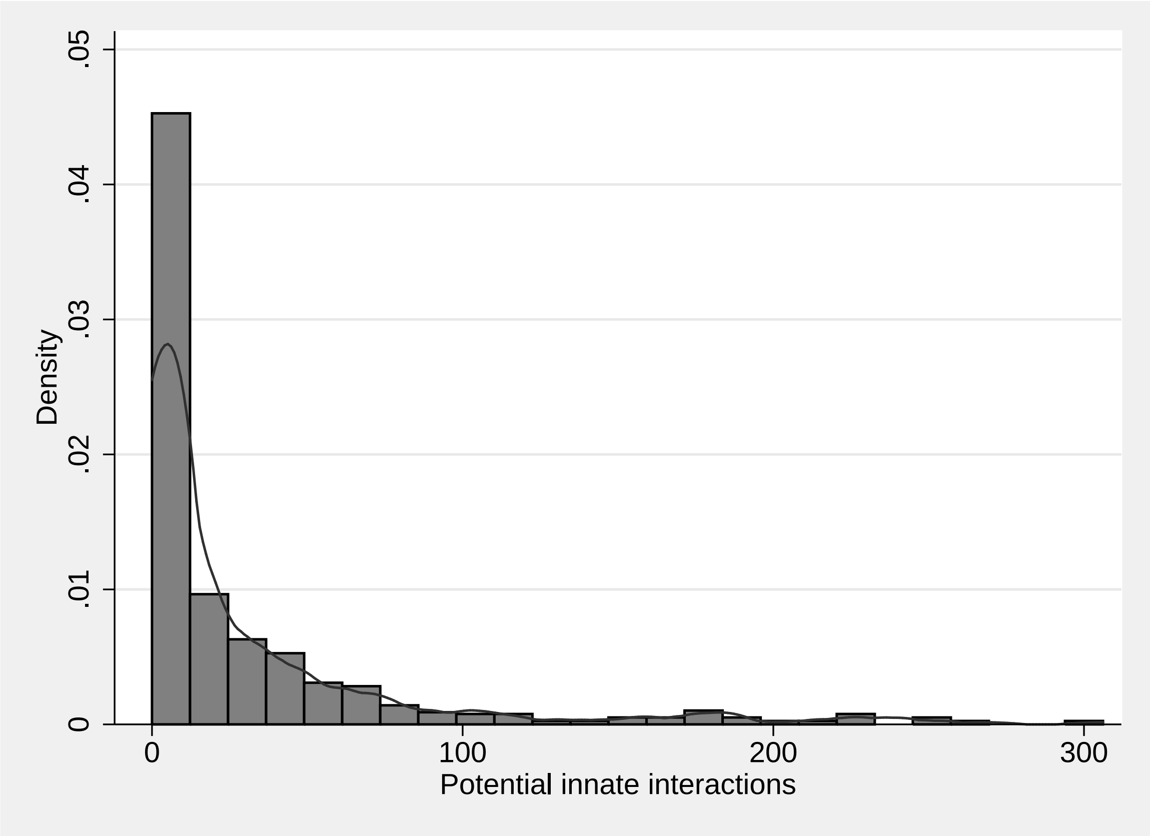

Figure 9: Density of Potential Innate Interactions

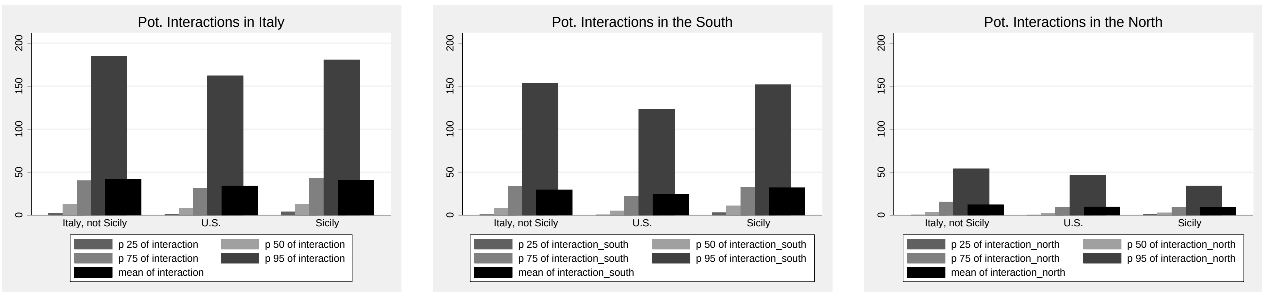

Figure 10: Distribution of the Potential Innate Interactions Index by Region of Birth

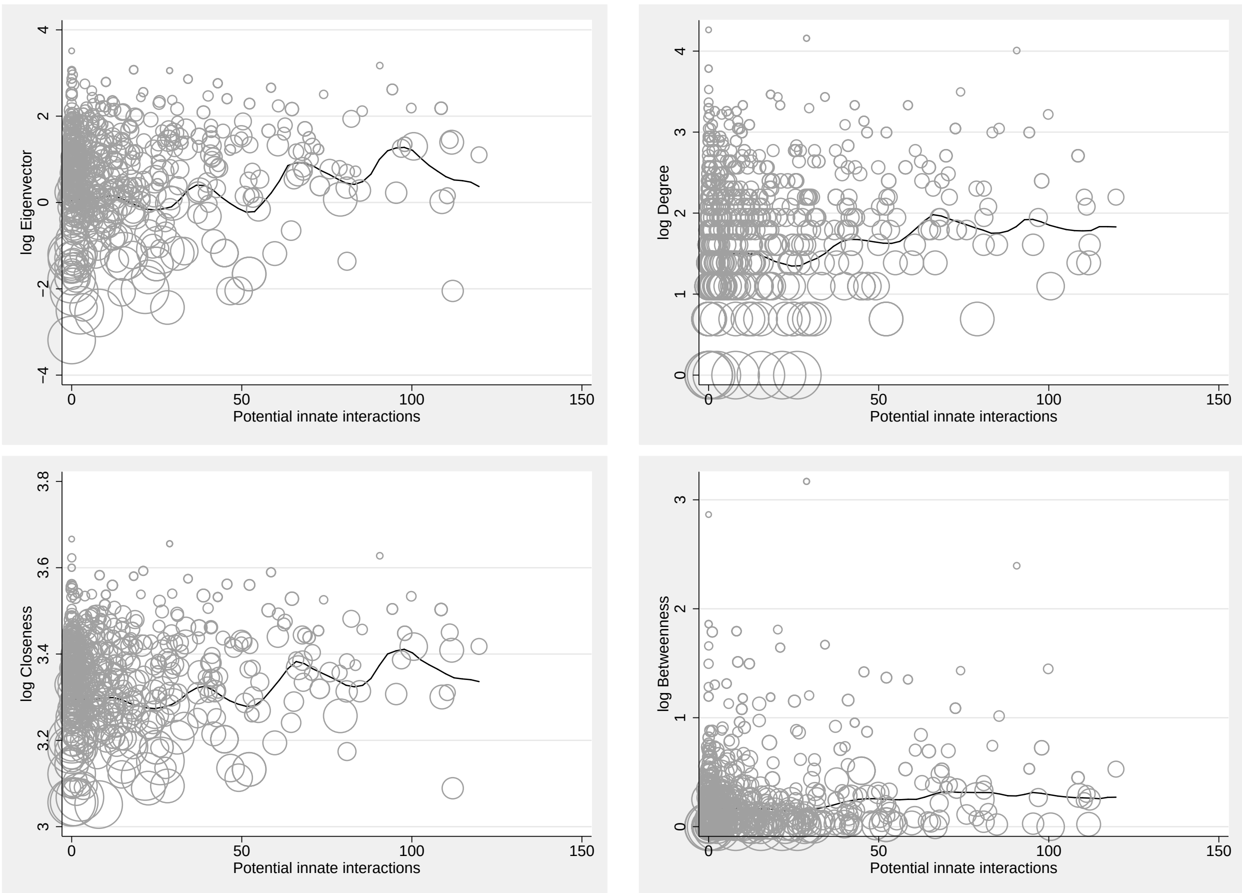

Figure 11: Network Centrality and Potential Innate Interactions Index (in logs)

Notes: The size of the circles is proportional to the sampling weight. The solid line corresponds to the local polynomial smoothing regression line (using the Epanechnikov kernel).

Table 1: Summary Statistics

	Unweighted		Weighted			
	Mean	St.Dev.	Mean	St.Dev.	Min	Max
Housing Value 1960	397,678	805,186	378,196	770,101	5,286	7,866,203
Degree	11.10	9.28	6.21	5.52	1	71
Eigenvector	12.77	14.12	6.59	8.31	0.05	100
Betweenness	4.94	9.33	1.90	4.21	0	100
Closeness	75.12	8.76	69.78	8.27	50.51	100
Potential innate interaction	36.18	76.79	26.10	51.59	0	654.02
Housing built after 1960	0.10	0.30	0.14	0.35	0	1
Year built unknown	0.12	0.33	0.12	0.33	0	1
Extended family members	1.58	1.01	1.30	0.73	1	6
Born outside Italy (mainly U.S.)	0.67	0.47	0.71	0.46	0	1
Born in Sicily	0.24	0.43	0.20	0.40	0	1
Age	48.63	7.59	48.20	7.57	24	72
Year of birth unknown	0.21	0.41	0.19	0.39	0	1
Height in feet	5.61	0.20	5.60	0.19	5	6.17
Weight in pounds	177.66	26.87	176.63	29.12	95	365
Age at first arrest	23.03	7.32	23.09	7.11	8	57
Never arrested	0.14	0.34	0.14	0.35	0	1
Connected wife	0.19	0.39	0.15	0.36	0	1
Married	0.80	0.40	0.76	0.43	0	1
Divorced	0.07	0.26	0.10	0.30	0	1
Number of children	1.07	1.47	1.06	1.44	0	8
Siblings	2.10	2.14	2.02	2.08	0	11
Types of crime committed	2.64	1.68	2.71	1.75	0	9
Number of businesses	1.08	1.01	1.00	0.94	0	5
Involved in drug dealing	0.56	0.50	0.59	0.49	0	1

Table 2: Summary Statistics of Legal Businesses

Variable	Mean	Std. Dev.	Mean	Std. Dev.
	unweighted		MC sampling	
Drugstores	0.18	0.38	0.17	0.37
Restaurants	0.09	0.31	0.09	0.29
Food companies	0.09	0.28	0.08	0.28
Manual laborer	0.07	0.26	0.09	0.29
Casinos	0.07	0.25	0.05	0.23
Real estate	0.05	0.23	0.06	0.24
Import export	0.05	0.22	0.05	0.22
Car dealer	0.05	0.22	0.04	0.20

Table 3: Mafia Bosses

	Mafia leader (weighted)		Mafia leader (unweighted)	
	No	Yes	No	Yes
Housing value	380,453	362,479	399,654	387,587
Narcotics	0.62	0.39	0.58	0.45
Betweenness	1.76	2.86	4.26	8.46
Closeness	69.63	70.85	74.51	78.23
Eigenvector	6.21	9.26	11.54	19.03
Degree	5.94	8.10	10.25	15.46

Table 4: Correlation Table

	log Clo.	log Bet.	log Eig.	log Deg.	Pot. Int.	Pot. Int. South
log Betweenness	0.533					
log Eigenvector	0.968	0.460				
log Degree	0.801	0.646	0.806			
Potential innate interactions	0.159	0.309	0.121	0.165		
Pot. Int. in the South	0.185	0.345	0.148	0.191	0.959	
Pot. Int. in the North	0.060	0.150	0.034	0.066	0.811	0.610

Notes: Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Housing value regressions and Closeness Centrality

	(1)	(2)	(3)	(4)	(5)
	log Housing value				
log Closeness	2.069***	2.524***	1.418***		
	(0.406)	(0.452)	(0.497)		
Closeness				0.036***	0.020***
				(0.007)	(0.007)
Housing built after 1960	0.100	0.054	0.048	0.051	0.045
	(0.156)	(0.159)	(0.157)	(0.160)	(0.158)
Year built unknown	-0.346***	-0.277**	-0.298**	-0.276**	-0.298**
	(0.121)	(0.122)	(0.140)	(0.122)	(0.140)
Extended family members		-0.216***	-0.067	-0.224***	-0.069
		(0.073)	(0.056)	(0.074)	(0.056)
Born outside Italy (mainly U.S.)		-0.089	-0.038	-0.085	-0.035
		(0.173)	(0.160)	(0.172)	(0.160)
Born in Sicily		-0.273	-0.173	-0.269	-0.169
		(0.188)	(0.161)	(0.188)	(0.161)
Age		-0.065	-0.076	-0.063	-0.075
		(0.074)	(0.075)	(0.074)	(0.075)
Age squared/100		0.067	0.082	0.065	0.081
		(0.081)	(0.080)	(0.081)	(0.080)
Year of birth unknown		-1.750	-1.935	-1.729	-1.920
		(1.602)	(1.663)	(1.610)	(1.664)
Height in feet		0.530*	0.224	0.536*	0.224
		(0.297)	(0.279)	(0.299)	(0.280)
Weight in pounds		-0.001	-0.000	-0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)
Age at first arrest		-0.013*	-0.016***	-0.013*	-0.016***
		(0.007)	(0.006)	(0.007)	(0.006)
Never arrested		-0.127	-0.181	-0.141	-0.188
		(0.204)	(0.183)	(0.205)	(0.183)
Married		-0.080	-0.000	-0.083	-0.001
		(0.151)	(0.138)	(0.151)	(0.139)
Divorced		-0.042	-0.005	-0.052	-0.010
		(0.222)	(0.184)	(0.222)	(0.184)
Number of children		-0.030	-0.062**	-0.031	-0.064**
		(0.030)	(0.028)	(0.030)	(0.028)
Siblings		0.016	-0.010	0.016	-0.010
		(0.025)	(0.025)	(0.026)	(0.025)
Types of crime committed		0.021	-0.002	0.019	-0.003
		(0.038)	(0.034)	(0.038)	(0.034)
Number of businesses		0.043	0.092**	0.043	0.092**
		(0.051)	(0.043)	(0.052)	(0.043)
Involved in drug dealing		0.346***	0.003	0.344***	-0.000
		(0.099)	(0.091)	(0.099)	(0.091)
State of residence fixed effects			X		X
Observations	641	641	637	641	637
R-squared	0.066	0.144	0.349	0.141	0.348

Notes: Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Housing value regressions with other centrality measures

	(1)	(2)	(3)	(4)	(5)	(6)
			log Housing Value			
log Eigenvector	0.184***	0.218***				
	(0.040)	(0.043)				
log Degree			0.148**	0.220***		
			(0.068)	(0.083)		
log Betweenness					-0.085	0.036
					(0.115)	(0.158)
Other Xs		X		X		X
Observations	641	641	641	641	641	641
R-squared	0.062	0.136	0.025	0.098	0.014	0.076

Notes: All regressions control for the housing variables. The additional regressors regressors ("Other Xs") are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Two Stage Least Squares Regressions

	(1)	(2)	(3)	(4)
Panel A: First stage regression	**log Closeness**	**log Eigenvector**	**log Degree**	**log Betweennes**
Potential innate interactions (in %)	0.021*	0.161	0.081	0.086**
	(0.011)	(0.114)	(0.069)	(0.042)
Zero potential innate interactions	-0.022	-0.351	-0.209	0.013
	(0.022)	(0.259)	(0.172)	(0.036)
R-squared	0.158	0.145	0.201	0.320
Panel B: Main regression		**log Housing value**		
log Closeness	8.343**			
	(4.144)			
log Eigenvector		0.754*		
		(0.412)		
log Degree			1.325*	
			(0.741)	
log Betweenness				1.745
				(1.501)
Observations	641	641	641	641
Endogeneity p-value	0.170	0.140	0.0986	0.187
Kleibergen-Paap rk Wald F statistic	2.670	2.101	1.705	2.058

Notes: Panel A shows the first stage regressions, Panel B the main log Housing value 2SLS regressions. Additional housing variables and the additional regressors regressors (“Other Xs”) are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Robustness Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Arrested gangsters		Everybody				
	OLS	IV	IV	IV	IV	OLS	IV
Panel A: First stage regression			**log Closeness centrality**				
Potential innate interactions (PII in %)		0.019*	0.023**	0.021			0.021**
		(0.010)	(0.011)	(0.029)			(0.011)
Zero PII		-0.038					-0.021
		(0.024)					(0.022)
PII squared				-0.002			
				(0.022)			
PII cube				0.001			
				(0.003)			
PII in Southern Italy					0.033**		
					(0.015)		
Zerp PII in Southern Italy					-0.019		
					(0.020)		
Connected wife							0.028*
							(0.016)
R-squared		0.162	0.155	0.155	0.160		0.165
Panel B: Main regression			**log Housing value**				
log Closeness	2.070***	9.358*	7.128*	6.819*	6.350**	2.486***	8.292**
	(0.482)	(5.222)	(4.272)	(3.573)	(3.196)	(0.453)	(4.097)
Connected wife						0.139	-0.022
						(0.143)	(0.228)
Observations	555	555	641	641	641	641	641
Kleibergen-Paap rk Wald F statistic		5.343	4.899	7.593	3.479		2.741

Notes: All regressions control for the additional housing variables and the additional regressors as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

A Online Appendix Figures

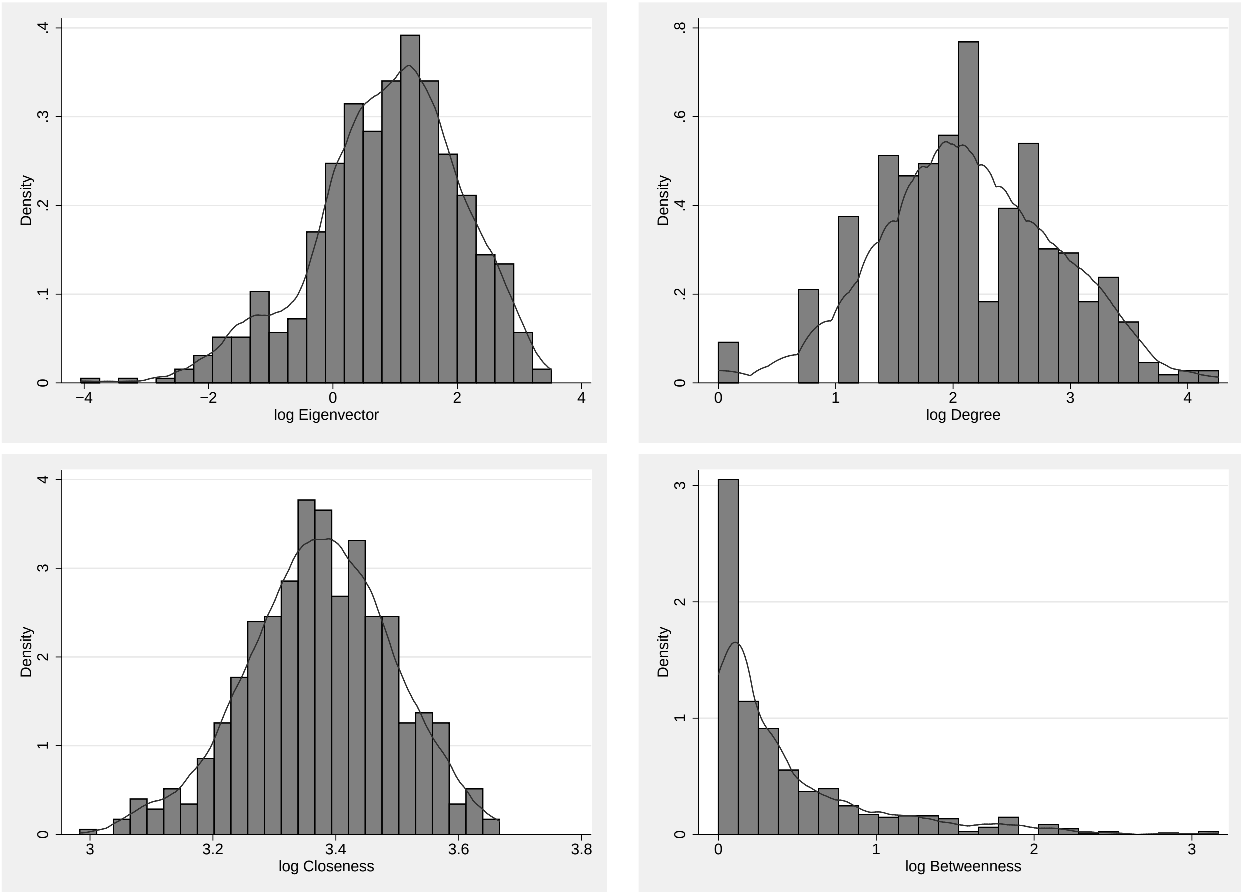

Figure 12: Densities of Log Centrality Indices

Notes: The density shows the entire distribution.

B Online Appendix Tables

Table 9: Testing for Heteroscedasticity: Squared Residual Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Squared residuals (× 100)							
	Closeness		Eigenvector		Degree		Betweenness	
	OLS	NLLS	OLS	NLLS	OLS	NLLS	OLS	NLLS
Average distance	-1.10%	-0.01%	-0.78%	-0.01%	-0.06%	0.00%	0.35%	0.00%
	(0.023)	(0.000)	(0.023)	(0.000)	(0.024)	(0.000)	(0.024)	(0.000)
Constant	132.1*	4.870***	123.7*	4.801***	108.3	4.683***	97.80	4.596***
	(62.569)	(0.618)	(63.007)	(0.618)	(65.183)	(0.611)	(65.587)	(0.609)
Observations	641	641	641	641	641	641	641	641

Notes: The residuals are based on Column 3 in Table 5 and Columns 2, 4, and 6 in Table 6. The non-linear least squares regressions (NLLS) model the squared residual as an exponential function of distance. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Place of Birth Heterogeneity

	(1)	(2)
	log Housing value	
log Closeness	0.683	1.375
	(0.880)	(0.894)
× born outside Italy	1.079	0.872
	(0.985)	(0.975)
× born in Italy	1.361	1.500
	(1.094)	(1.126)
Other regressors		X
Observations	641	641
R-squared	0.070	0.134

Notes: All regressions control for the housing variables. The additional regressors regressors ("Other Xs") are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Housing value regressions without weighting for the sampling design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log Housing value							
log Closeness	1.504***	2.299***						
	(0.328)	(0.403)						
log Eigenvector			0.152***	0.212***				
			(0.034)	(0.040)				
log Degree					0.042	0.136**		
					(0.054)	(0.067)		
log Betweenness							-0.049	0.039
							(0.070)	(0.092)
Other regressors		X		X		X		X
Observations	641	641	641	641	641	641	641	641
R-squared	0.046	0.132	0.046	0.128	0.020	0.093	0.020	0.087

Notes: All regressions control for the housing variables. The additional regressors regressors ("Other Xs") are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Full First Stage Regressions: Centrality Measures and the Potential Innate Interactions Based on Surnames

	(1) log Closeness	(2) log Eigenvector	(3) log Degree	(4) log Betweennes
Potential innate interactions (in %)	0.021*	0.161	0.081	0.086**
	(0.011)	(0.114)	(0.069)	(0.042)
Zero potential innate interactions	-0.022	-0.351	-0.209	0.013
	(0.022)	(0.259)	(0.172)	(0.036)
Housing built after 1960	-0.036*	-0.444**	-0.294**	-0.060**
	(0.019)	(0.203)	(0.126)	(0.026)
Year built unknown	-0.024	-0.170	-0.074	-0.033
	(0.022)	(0.231)	(0.145)	(0.032)
Extended family members	0.033**	0.271*	0.298***	0.202***
	(0.014)	(0.146)	(0.085)	(0.033)
Born outside Italy (mainly U.S.)	-0.004	-0.041	-0.001	-0.017
	(0.032)	(0.360)	(0.193)	(0.036)
Born in Sicily	0.020	0.257	0.087	0.045
	(0.031)	(0.347)	(0.199)	(0.040)
Age	0.006	0.038	0.002	0.013
	(0.009)	(0.102)	(0.059)	(0.017)
Age squared/100	-0.005	-0.029	0.005	-0.010
	(0.009)	(0.107)	(0.063)	(0.018)
Year of birth unknown	0.140	0.685	0.283	0.380
	(0.208)	(2.351)	(1.365)	(0.389)
Height in feet	0.070*	0.828*	0.266	0.041
	(0.037)	(0.425)	(0.215)	(0.058)
Weight in pounds	-0.000	-0.002	0.001	0.000
	(0.000)	(0.005)	(0.002)	(0.000)
Age at first arrest	-0.001	-0.015	0.001	0.000
	(0.001)	(0.011)	(0.006)	(0.001)
Never arrested	-0.049	-0.613*	-0.071	0.026
	(0.031)	(0.352)	(0.177)	(0.042)
Married	0.013	0.155	0.175	0.006
	(0.018)	(0.203)	(0.128)	(0.029)
Divorced	-0.029	-0.383	-0.193	-0.002
	(0.029)	(0.334)	(0.216)	(0.046)
Number of children	0.001	-0.010	-0.042	0.004
	(0.006)	(0.061)	(0.033)	(0.007)
Siblings	0.005	0.044	0.029	0.010**
	(0.003)	(0.034)	(0.019)	(0.005)
Types of crime committed	-0.010*	-0.086	-0.026	-0.002
	(0.006)	(0.062)	(0.037)	(0.007)
Number of businesses	0.010*	0.116*	0.058*	0.024**
	(0.006)	(0.061)	(0.033)	(0.010)
Involved in drug dealing	-0.004	-0.132	-0.083	0.031
	(0.015)	(0.167)	(0.106)	(0.024)
Housing variables				
Observations	641	641	641	641
R-squared	0.158	0.145	0.201	0.320
Kleibergen-Paap rk Wald F statistic	2.670	2.101	1.705	8.557
F-stat on potential innate interactions	3.782	2.001	1.388	4.087

Notes: All regressions control for the housing variables. The additional regressors regressors ("Other Xs") are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Full IV Regressions: Centrality Measures and the Potential Innate Interactions Based on Surnames

	(1)	(2)	(3)	(4)
		log Housing value		
log Closeness	8.343**			
	(4.144)			
log Eigenvector		0.754*		
		(0.412)		
log Degree			1.325*	
			(0.741)	
log Betweenness				1.745
				(1.501)
Housing built after 1960	0.243	0.279	0.333	0.066
	(0.220)	(0.250)	(0.288)	(0.196)
Year built unknown	-0.149	-0.225	-0.256	-0.273*
	(0.211)	(0.196)	(0.200)	(0.146)
Extended family members	-0.444**	-0.365**	-0.553**	-0.509
	(0.184)	(0.153)	(0.260)	(0.365)
Born outside Italy (mainly U.S.)	-0.040	-0.038	-0.066	-0.074
	(0.271)	(0.272)	(0.270)	(0.189)
Born in Sicily	-0.389	-0.413	-0.334	-0.300
	(0.291)	(0.301)	(0.297)	(0.216)
Age	-0.102	-0.082	-0.056	-0.070
	(0.086)	(0.084)	(0.093)	(0.085)
Age squared/100	0.096	0.080	0.053	0.071
	(0.093)	(0.093)	(0.103)	(0.092)
Year of birth unknown	-2.627	-2.008	-1.871	-2.027
	(1.893)	(1.807)	(2.050)	(1.923)
Height in feet	0.127	0.101	0.375	0.619*
	(0.457)	(0.514)	(0.441)	(0.327)
Weight in pounds	-0.001	-0.000	-0.004	-0.002
	(0.002)	(0.003)	(0.002)	(0.003)
Age at first arrest	-0.006	-0.005	-0.018*	-0.016**
	(0.009)	(0.010)	(0.009)	(0.008)
Never arrested	0.144	0.200	-0.167	-0.303
	(0.305)	(0.327)	(0.260)	(0.243)
Married	-0.127	-0.146	-0.263	-0.039
	(0.195)	(0.203)	(0.251)	(0.153)
Divorced	0.176	0.235	0.202	-0.111
	(0.325)	(0.359)	(0.419)	(0.241)
Number of children	-0.033	-0.021	0.027	-0.034
	(0.046)	(0.046)	(0.054)	(0.033)
Siblings	-0.011	-0.003	-0.009	0.013
	(0.038)	(0.039)	(0.045)	(0.031)
Types of crime committed	0.076	0.058	0.028	-0.003
	(0.063)	(0.056)	(0.054)	(0.041)
Number of businesses	-0.009	-0.012	-0.001	0.026
	(0.072)	(0.074)	(0.075)	(0.069)
Involved in drug dealing	0.368***	0.438***	0.449***	0.279**
	(0.128)	(0.132)	(0.154)	(0.117)
Observations	641	641	641	641

Notes: The additional housing variables are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Reduced Form Regressions: log Housing values and Closeness Centrality

	(1)	(2)	(3)
		log Housing value	
Sample:	Evereybody	Arrested gangsters	Everybody
Potential innate interactions (PII in			
	(0.105)	(0.111)	
Zero PII	-0.249	-0.259	
	(0.213)	(0.236)	
PII in Southern Italy			0.241*
			(0.130)
Zero PII in Southern Italy			-0.214
			(0.205)
Housing built after 1960	-0.057	0.006	0.024
	(0.167)	(0.184)	(0.184)
Year built unknown	-0.352***	-0.320**	-0.313**
	(0.122)	(0.131)	(0.131)
Extended family members	-0.164*	-0.211**	-0.210**
	(0.099)	(0.089)	(0.089)
Born outside Italy (mainly U.S.)	-0.069	-0.064	-0.071
	(0.173)	(0.184)	(0.188)
Born in Sicily	-0.219	-0.319*	-0.334*
	(0.184)	(0.193)	(0.197)
Age	-0.053	-0.037	-0.033
	(0.079)	(0.084)	(0.084)
Age squared/100	0.058	0.039	0.035
	(0.086)	(0.090)	(0.090)
Year of birth unknown	-1.484	-1.008	-0.922
	(1.732)	(1.890)	(1.893)
Height in feet	0.722**	0.503	0.515
	(0.314)	(0.335)	(0.338)
Weight in pounds	-0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)
Age at first arrest	-0.016**	-0.012	-0.012
	(0.008)	(0.009)	(0.009)
Never arrested	-0.263		
	(0.229)		
Married	-0.026	-0.054	-0.058
	(0.153)	(0.172)	(0.173)
Divorced	-0.055	-0.072	-0.075
	(0.232)	(0.249)	(0.248)
Number of children	-0.029	-0.010	-0.010
	(0.032)	(0.034)	(0.034)
Siblings	0.030	0.061**	0.060**
	(0.027)	(0.027)	(0.027)
Types of crime committed	-0.007	0.012	0.010
	(0.039)	(0.041)	(0.042)
Number of businesses	0.076	0.051	0.051
	(0.054)	(0.059)	(0.059)
Involved in drug dealing	0.338***	0.347***	0.353***
	(0.104)	(0.111)	(0.112)
Observations	641	554	554
R-squared	0.087	0.107	0.104
Anderson and Rubin p value	0.168	0.0903	0.0838

Notes: The additional housing variables are the same as in Table 5. Clustered (by surname) standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.