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Social networks, information and health care utilization: Evidence from undocumented immigrants in Milan

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Abstract

This paper uses a novel dataset and research design to examine the effects of information networks on immigrants' access to health care. The dataset consists of an unusually large sample of undocumented immigrants and contains a direct indicator of information networks—whether an immigrant was referred to health care opportunities by a strong social tie (relative or friend). This measure allows to overcome some of the major identification issues that afflict most of the existing literature on network effects and to concentrate on one of the channels through which social contacts might operate. The analysis focuses on the time spent in Italy before an immigrant first receives medical assistance. Estimates indicate that networks significantly foster health care utilization: after controlling for all available individual characteristics and for ethnic heterogeneity, I find that relying on a strong social tie reduces the time to visit by 30%. The effect of information networks is stable across specifications and it is relatively large. Further investigation seems to confirm the quantitative importance of networks as an information device.

JEL classification: Z13; J15; I12

Keywords: Network effects; Undocumented immigrants; Health utilization

1. Introduction

Recent studies have documented the existence of sizeable differences in welfare utilization between ethnic groups, which tend to persist across generations, thus posing important policy issues.[1] These differences reveal that social programs may not be fully successful in reaching the groups they are targeted to as well as raising relevant equity problems.

Racial and ethnic differences in take-up rates are in part related to immigrants' access to welfare, since in most countries a large fraction of minorities consists of immigrants and because similar transmission mechanisms may be

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[1] See, for instance, Borjas and Sueyoshy (1997) and Duggan and Kearney (2005). Currie (2006) reviews the literature on the take-up of social programs in the US and the UK. She documents that take-up rates vary substantially between ethnicities. See also Currie and Hotz (2004) on racial differences in access to health care. For brevity, in this introduction I will use welfare and social assistance interchangeably. Moreover, with welfare programs I refer to both monetary and in kind transfer programs.

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at work. When immigrants are considered, the emphasis is often shifted from exclusion to dependency. The principal concern is that excessive welfare utilization could hinder the financial sustainability of existing social programs. From previous studies we know that immigrants are more likely to be eligible for welfare and their take-up rates increase with permanence in the host country. Moreover, welfare use differs remarkably by national origin[2] (to ease notation, in what follows I adopt the standard terminology and country of origin will often be referred to as ethnicity). The present paper focuses on one of the suggested mechanisms through which welfare cultures may be transmitted across individuals and generations, namely social networks.

Sociologists have long emphasized the importance of networks in shaping individuals' behavior. Insights from the sociological literature have recently attracted considerable interest from economists and they have been applied to several important areas of economic research.[3] Concerning welfare utilization decisions, networks work through two main channels: they can supply information (on the availability of services, their location, eligibility criteria, procedures of application and other relevant details) and they can provide peer pressure and alter the demand for the service (this is often referred to as the norm channel, or stigma effect in the take-up literature). It is worth stressing that the distinction between norms and information is crucial for policy purposes, since the two mechanisms may have very different policy implications. For example, if the information channel is relatively more important, policies aimed at increasing the use of primary health care by immigrants or minorities could easily exploit the multiplier effect of networks. This can be done, for instance, by advertising the program in immigrants' meeting areas and newspapers, and providing the related information in different foreign languages. The consequences of such policies could be much more unpredictable if, instead, networks mainly work through ethnic norms. Section 3.1 further elaborates on the distinction between the two mechanisms.

Despite the great emphasis placed in the literature on network effects among immigrants, their quantification is extremely problematic. One of the reasons is that very few datasets contain information on actual social contacts. A common practice in empirical research is to proxy the availability of networks with some measure of spatial concentration of ethnic minorities or immigrants.[4] The underlying assumption is that individuals mainly interact with geographically close people of the same ethnicity. A major complication of this research design comes from the fact that a positive correlation between an individual outcome and the average behavior of his/her reference group does not provide conclusive evidence of network effects and the well understood reflection problem must be addressed.[5]

This approach has been fruitfully used to study welfare and health assistance participation.[6] Bertrand et al. (2000) look at the use of public assistance across immigrants in the US. They measure the quantity of networks (contact availability) with the number of people in one's local area who speak the same language, and interact this variable with the average welfare use of the language group (quality of the network). Deri (2005) applies the same approach

[2] On welfare use by immigrants see, among the others, Bean et al. (1997), Borjas and Hilton (1996), Borjas and Trejo (1991), Riphahn (2004). Borjas and Trejo (1991) document the assimilation into the welfare system: the longer an immigrant lives in the destination country, the more likely the person is to receive assistance—see also Baker and Benjamin (1995) for Canada and Riphahn (2004) for Germany. Leclere et al. (1994) observe that duration of residence in the US has a strong impact on the access and the volume of health care for immigrants. Borjas and Trejo (1993) find significant effects of the country of origin for social assistance receipt. Borjas and Hilton (1996) show that welfare benefits received by earlier waves of immigrants influence the type of benefit received by newly arrived immigrants; they suggest that information about welfare programs is transmitted within ethnic networks.

[3] Almost all the studies on social networks reviewed in this introduction provide an overview of the various applications of network relationships in economics—see also Topa (2001) and references cited therein. Examples of the extensive sociological literature on social networks among immigrants and ethnic minorities are Enchautegui (2002), Menjivar (2000), Portes (1995), Portes and Sensenbrenner (1993), Sanders et al. (2002).

[4] As a consequence, the literature on network effects greatly overlaps with the literature on neighborhood effects and ethnic or language enclaves.

[5] See Manski (1993, 2000).

[6] It has been also applied to address the effects of ethnic networks on labor market outcomes [see, among the others, Cutler and Glaeser (1997), Damm and Rosholm (2005), Edin et al. (2003), Munshi (2003)]. Oreopoulos (2003) looks at the long run neighborhood effects on employment, earnings and welfare participation rates. Spatial proximity has been recently used by Bayer et al. (2005) to identify informal networks in the labor market. Obviously, labor market outcomes and welfare use are intimately related areas of research. However, a review of this literature is far beyond the scope of this paper: as Calvò-Armengol and Jackson (2004) notice, ethnic and racial inequality in the labor market is, indeed, one of the most extensively studied issues in labor economics. Ioannides and Loury (2004) survey the literature on job information networks and they highlight the existence of important racial and ethnic differences in the use of friends and relatives to search for jobs and in the productivity of job search through strong social contacts.

to study health service utilization in Canada.[7] Aizer and Currie (2004) look at publicly funded prenatal care and use mothers' racial or ethnic concentration at 5-digit zip codes. All these studies find that networks are important in shaping participation in publicly provided programs. Åslund and Fredriksson (2005) look at the effect of spatial concentration of immigrants on welfare using a natural experiment, the Swedish Refugee Placement Policy, and conclude that only the quality of the contact matters.

An important limitation of these studies is that they say little on how networks actually work. In particular, it is not trivial to assess the relative importance of the two channels – information and norms – through which social contacts may affect individual behavior. Åslund and Fredriksson (2005) argue that in their setting the information channel is relatively unimportant, since all refugee immigrants were placed on welfare by default and should therefore already know the working of the system. Aizer and Currie (2004) indirectly confirm the minor role of information sharing. They find similar network effects between women who had previously used the program and those who were first-time users. These results are puzzling, as other evidence suggests that participation in social programs is, indeed, greatly shaped by (lack of) information.[8]

This paper attempts to contribute to the existing literature by focusing on the role of information networks in influencing immigrants' access to primary health care.[9] The paper uses a novel dataset and research design. The dataset was collected in Milan between April 2000 and October 2001 by Naga, a volunteer association offering free medical care to undocumented immigrants.[10] The data present several features – which I discuss in more detail in Sections 2 and 3 – that determine both the empirical strategy and the scope of the analysis.

First of all, individual files report whether the immigrant became acquainted with Naga services through a strong network (friend or relative).[11] Therefore, in contrast to the other existing studies, I do observe a social contact, but only if it was a source of information. This allows me to overcome many identification issues characterizing previous studies and to focus on one of the two channels through which social networks might operate.

Second, I only observe immigrants if they receive health care. This has two major consequences: it causes serious selection problems, which I discuss below, and it forces me to study health service utilization by focusing on the time required for an immigrant to get medical assistance.

Finally, the sample includes only irregular immigrants. I believe that the study of undocumented immigrants' network effects is valuable in itself[12] and, as a byproduct, the paper provides new evidence on this hidden phenomenon. However, it also limits the scope of the analysis and its direct comparison to the existing literature. Indeed, as I discuss in Section 3.1, reliance on strong networks is likely to be particularly important for individuals in the sample.

Results show that, after controlling for all available individual characteristics and for country of origin fixed effects, relying on a strong social tie to get information on Naga reduces the time to visit by about 30%. The effect of information networks is stable across specifications and it is relatively large. Further investigation seems to confirm the quantitative relevance of networks as an information device. In particular, the network effect decreases with the level of education. This fact supports the intuition that – to the extent that education is correlated with the immigrant's ability to speak foreign languages, to learn about institutional details and, in general, to exploit more and different information channels – immigrants with a lower education level might rely more heavily on strong social ties to access information.

The paper proceeds as follows. Section 2 presents the institutional context, the data, and the descriptive statistics. Section 3 illustrates the research design used to identify the effect of information networks and the regression specification. Section 4 provides the results. Finally, Section 5 concludes.

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7 McDonald and Kennedy (2005) employ Bertrand et al. (2000)'s method to study the effect of social networks on the incidence of being overweight and obese among ethnic minorities in Canada; obviously, excess weight is linked to several health risks and, consequently, it can affect health service utilization.

8 See Daponte et al. (1999) and Aizer (2004). Heckman and Smith (2004) propose a decomposition of the participation process in multiple stages. They find that the difference in participation in programs between Blacks and Hispanics is mostly determined by whether the individuals are aware of the program or not. In a different context – a randomized experiment to study employees' decision to enroll on a retirement plan – Duflo and Saez (2003) find evidence that information is multiplied through social interaction.

9 Notice, incidentally, that access to primary health care has additional policy implications: not only can it be crucial in deterring epidemics (health externality), but it is also efficient at the individual level, reducing the cost of treatment with respect to later interventions.

10 The term undocumented immigrants denotes people residing in Italy without the necessary authorizations (see the definition of "migration in abusive condition", ILO Convention no. 143, 1975). The literature – and this paper – also refers to them as illegal or irregular migrants.

11 Following a common terminology in the sociological literature, here strong social networks denote friends and relatives—see also footnote 23.

12 To the best of my knowledge, this is the only study which can address the issue.

2. Data and descriptive statistics

2.1. Undocumented immigrants and health care in Italy

Undocumented immigration has become a major concern in most developed countries. In Italy, according to the last available official estimate[13] between 23 and 27% of foreign immigrants were undocumented. Unofficial estimates for 2003 range between 200,000 and 800,000 irregular presences (7%–24% of immigrants).[14] Lombardy, the region where Milan is located, has the highest share of immigrants and Milan has the largest foreign-born population in Italy, after Rome.

Immigrants' access to health care in Italy has been subject to several reforms in the last decades. At the moment, regular immigrants are completely integrated in the National Health Service. On the other hand, for undocumented foreigners access to health care is restricted. In 1998 the "Turco-Napolitano" law[15] has established that irregular immigrants should be guaranteed the following types of treatments: emergency and first aid; the so-called "essential treatments" (all pathologies not immediately dangerous, but which could worsen in the future); pre and post-natal care; pediatrics and geriatrics. However, we observe some regional variability in the implementation of such prescriptions, given that the Italian National Health Service is decentralized at the regional level. In particular, at the moment Lombardy has not yet organized a system of primary care provision for irregular aliens and this was, *a fortiori*, the case in 2001. Apart from primary care being totally left to the responsibility of voluntary associations, access to secondary care was also limited, and the only health service that was provided to irregular immigrants was emergency and first aid.

2.2. Data source

The present study uses a unique dataset collected by Naga, a voluntary association which offers free primary care to irregular immigrants. Naga is a large organization, supplying a daily average of over 60 visits, 5 days a week. Being located in Milan, its services are used by residents of the city or of its close suburbs. The association does not discriminate immigrants in any way according to their nationality and/or religion. There is no eligibility issue. If a regular immigrant reaches Naga, she/he is redirected to the National Health Service and therefore the sample does not include regular immigrants.

In order to facilitate the doctors' tasks, Naga volunteers carry out short interviews with the immigrants during their first visit completing a file with personal information. The information available on electronic format was collected between April 2000 and October 2001 and contains a snapshot description of the immigrant's social and economic situation at the time of the visit. It includes: country of origin, sex, date of birth, date of arrival in Italy, date of visit, marital status, number of children, education, current employment, occupation in the home country, knowledge of Italian, accommodation, and Naga contact (who introduced him/her to Naga).

The initial sample consists of 10,571 observations. I eliminate individuals for whom I have no information on the date of visit and/or arrival in Italy (246 observations). I also drop children below age 15 (71 observations). The final sample described in this section consists of 10,254 individuals. The number of missing observations varies greatly across items; in particular, the Naga contact variable, which is at the core of my analysis, is missing for an additional 786 individuals. For the regression analysis I will impose some further sample restrictions, detailed in Section 4.1.

The main shortcoming of the dataset is that it is a non-random sample of irregular immigrants, as it includes only individuals that choose to visit Naga for medical care, and several factors influence this event. In particular, individuals of a lower socio-economic status may be over-represented for a number of reasons. The most obvious one is that individuals must be seeking health assistance, which, in turn, is clearly linked to their socioeconomic conditions. Second, poor immigrants cannot afford the cost of a private doctor and, therefore, their only chance of getting primary medical care is through Naga, or other voluntary associations. Finally, Naga is open only during working hours, limiting

[13] Ministero dell'Interno (1998), "Relazione sulla presenza straniera in Italia e sulle situazioni di irregolarità".
[14] See Caritas/Migrantes (2004). The wide range of different estimates confirms the fact that the phenomenon is – by its very nature – extremely difficult to quantify.
[15] D.Lgs. 25 luglio 1998, n. 286.

Table 1
Regional composition (percentage)

Region	Naga	Ismu (Milan) undocumented	Ismu (Milan) regular and undocumented
Eastern Europe	15.7	13.4	10.4
Asia	12.7	23.2	38.5
North Africa	18.8	22.3	21.9
Sub-Saharan Africa	8.3	11.8	9.9
Latin America	44.5	29.3	19.6

the possibility for employed immigrants to take advantage of the service (notice, in addition, that being sick could prevent individuals from working). Overall, these factors tend to select immigrants in the sample according to their income (poorer) and employment status (jobless). Further selection into Naga can originate from cultural factors (in particular trust in Western medicine[16] as compared to other styles of remedies) and from the characteristics of the migratory pattern (well established communities might provide their members with alternative resources and services to deal with health needs, but also with more information about Naga). I try to address these issues in the regression analysis by controlling for individual and country specific characteristics.

2.3. Descriptive statistics

Immigrants in the sample are from 95 different countries, although 75% of them originate from just 9 countries. Table 1 reports the composition of the sample by region of origin.[17] It also provides the composition of the Ismu[18] estimates in 2001, both for undocumented only and for all immigrants in Milan. The differences between columns 1 and 2 are substantial: according to Ismu, immigrants from Latin America account for 29.3% of irregular immigrants, but represent 44.5% of users of the Naga services. Asians, on the contrary, are underrepresented in the Naga sample.

It is important to stress that these discrepancies in the ethnic composition of the two samples do not imply that the Ismu survey correctly estimates the underlying population of undocumented immigrants whereas the Naga sample suffers from a selection bias. In fact, it should be acknowledged that the universe of undocumented immigrants is by definition a hidden one and these figures illustrate the intrinsic difficulties in conducting any empirical study in this area. For example, Ismu estimates no presence in Milan of either regular or undocumented immigrants from 58 countries represented in the Naga sample.[19] Devillanova and Frattini (2006) argue that the sampling strategy adopted by Ismu performs relatively poorly for recently arrived communities, characterized by a high share of undocumented immigrants.[20]

Table 2 provides the main descriptive statistics, which are mostly self-explanatory. Here I only emphasize a few key facts.

Individuals are quite evenly distributed between sexes, with a slightly higher prevalence of men (58%). The gender composition is characterized by dramatic differences across areas of origin, with a higher frequency of men in all areas except Latin America (Eastern Europe is more evenly balanced). On average individuals are young, with a mean age of 32 years (the median age is 30.2 years). North Africa has the youngest population; on the other extreme there are immigrants from Latin America.

[16] This could be the case for the Chinese community, which is underrepresented in the sample.

[17] See Appendix A for the definition of regions.

[18] Ismu is an autonomous and independent organization located in Milan, promoting studies, research and projects on multi-ethnic and multi-cultural society, and focusing in particular on the phenomenon of international migration. The data come from "L'immigrazione straniera in Lombardia. La prima indagine regionale", Osservatorio Regionale per l'integrazione e la multietnicità, 2002. The report is freely available at www.ismu.org.

[19] Only for 3 of these 58 countries (Bosnia, Burkina Faso and Bolivia) Ismu estimates a positive presence in Lombardy. Five of them (Cameroon, Congo, Bolivia, Moldova and Ukraine) have more than 26 observations and are included in the baseline regression analysis below; one of them (Ukraine) accounts for 3.1% of the Naga sample (320 observations).

[20] The sampling strategy adopted by Ismu is based on the identification of immigrants' meeting areas, such as places of worship, recreation centers and so forth. Indeed, the identification of such areas is crucial and it is especially challenging for the recently established ethnic communities. The Ismu estimates are based upon a sample survey referred to the universe of the foreigners present in Lombardy in mid-2001. The sample size is fixed at 7800 units in the whole region, which includes 342 different municipalities; 1153 interviews were conducted in Milan.

Table 2
Descriptive statistics, by region

Variable	Number of observations	Whole sample		Eastern Europe		Asia		North Africa		Sub-Saharan Africa		Latin America	
		mean	Sd. Dev.	mean	Sd. Dev.	mean	Sd. Dev.	mean	Sd. Dev.	mean	Sd. Dev.	mean	Sd. Dev.
Man	10,254	0.58	0.49	0.54	0.50	0.73	0.44	0.96	0.20	0.70	0.46	0.36	0.48
Age at visit (years)	10,230	31.87	9.30	32.11	10.06	31.99	9.41	29.74	7.55	31.87	9.78	32.65	9.43
Time to visit (months)	10,254	18.51	26.46	16.77	20.83	22.34	29.78	29.70	38.69	21.02	31.68	12.85	16.04
Married	10,013	0.46	0.50	0.55	0.50	0.54	0.50	0.28	0.45	0.35	0.48	0.51	0.50
Single	10,013	0.48	0.50	0.38	0.49	0.43	0.50	0.69	0.46	0.62	0.49	0.41	0.49
Number of children	10,254	1.09	1.52	1.00	1.26	0.97	1.44	0.58	1.31	0.91	1.84	1.40	1.57
% with children (parent)	10,254	0.47	0.50	0.52	0.50	0.45	0.50	0.24	0.43	0.32	0.47	0.60	0.49
Number of cohabitants	8,260	4.29	2.12	3.54	1.89	4.08	1.77	3.95	1.86	3.74	2.01	4.77	2.26
Accommodation													
Employer	9,141	0.06	0.24	0.10	0.30	0.04	0.19	0.01	0.07	0.02	0.14	0.09	0.29
Friends/relatives	9,141	0.75	0.43	0.61	0.49	0.83	0.38	0.76	0.43	0.77	0.42	0.78	0.41
Own	9,141	0.10	0.30	0.09	0.28	0.09	0.29	0.07	0.26	0.10	0.31	0.11	0.32
Other	9,141	0.08	0.28	0.21	0.41	0.04	0.20	0.16	0.37	0.11	0.31	0.01	0.12
Education													
No education	9,916	0.03	0.18	0.02	0.15	0.02	0.15	0.09	0.29	0.08	0.27	0.01	0.08
Primary	9,916	0.10	0.30	0.06	0.23	0.11	0.31	0.15	0.35	0.16	0.37	0.08	0.27
Secondary	9,916	0.35	0.48	0.40	0.49	0.45	0.50	0.31	0.46	0.30	0.46	0.33	0.47
High	9,916	0.42	0.49	0.40	0.49	0.35	0.48	0.35	0.48	0.36	0.48	0.48	0.50
University	9,916	0.10	0.30	0.12	0.32	0.07	0.26	0.10	0.30	0.10	0.30	0.11	0.31
Italian	10,254	0.51	0.50	0.57	0.49	0.37	0.48	0.46	0.50	0.46	0.50	0.55	0.50
Out of the labor force	9,946	0.02	0.12	0.02	0.14	0.02	0.12	0.01	0.09	0.02	0.14	0.02	0.13
Unemployed	9,946	0.46	0.50	0.40	0.49	0.48	0.50	0.47	0.50	0.64	0.48	0.44	0.50
Permanent employment	9,946	0.26	0.44	0.33	0.47	0.27	0.44	0.21	0.41	0.14	0.34	0.28	0.45
Temporary employment	9,946	0.26	0.44	0.25	0.43	0.24	0.43	0.32	0.46	0.20	0.40	0.26	0.44
Network	9,468	0.83	0.37	0.72	0.45	0.88	0.33	0.78	0.42	0.78	0.41	0.89	0.31

Table 3
Educational attainment, by region and gender

Education	Eastern Europe			Asia			North Africa			Sub-Saharan Africa			Latin America		
	F	M	Total	F	M	Total	F	M	Total	F	M	Total	F	M	Total
Whole sample															
No education	2.8	1.8	2.2	3.5	2.0	2.4	17.7	8.9	9.3	6.6	8.6	8.0	0.7	0.7	0.7
Primary	3.7	7.4	5.7	12.7	10.2	10.9	12.7	14.9	14.8	16.9	15.6	16.0	8.4	7.1	7.9
Secondary	36.0	43.4	40.0	43.4	45.3	44.8	32.9	31.2	31.0	33.9	28.2	29.9	32.1	34.0	32.8
High	40.8	40.0	40.4	31.3	36.2	34.9	31.6	34.7	34.6	39.7	34.8	36.3	47.8	47.4	47.7
University	16.7	7.4	11.6	9.1	6.2	7.0	5.1	10.2	10.0	2.9	12.7	9.8	11.0	10.9	11.0
Age 25–64															
No education	2.8	1.6	2.2	4.1	2.5	2.9	23.6	10.3	10.8	8.0	9.4	9.0	0.7	0.9	0.8
Primary	3.1	7.0	5.1	14.5	9.9	11.2	12.7	15.3	15.2	18.7	15.7	15.2	9.1	7.5	8.5
Secondary	34.3	40.4	37.4	39.2	42.6	41.6	23.6	27.3	27.1	33.3	27.1	28.6	31.0	33.0	31.7
High	39.5	41.1	40.3	31.7	37.6	35.9	34.5	35.0	35.0	37.3	34.1	34.9	46.3	46.4	46.3
University	20.3	9.8	14.9	10.4	7.4	8.3	5.4	12.1	11.8	2.7	13.8	11.0	12.8	12.2	12.6

One key variable in the following analysis is going to be the time to visit. The average time spent in Italy before the immigrant first gets to Naga is 18.5 months, but there are sizeable differences across areas.

Forty-six percent of the sample is married and about 6% is either separated or widowed. About half of the sample has offspring (parent is an indicator for having at least one child), but I do not know if children are in Italy or if they were left in the home country. Again, figures greatly differ across regions. For example, most Africans have no children (76% of North Africans and 68% of Sub-Saharan Africans) while the majority of Eastern Europeans and Latin Americans have at least one child.

The dataset reports some crude information on accommodation (whether the individual lives in her/his own house, with the employer, or with friends or relatives; the residual category – other – includes dormitory and homeless). Most immigrants live together with friends or relatives. The share of people living with their employer is higher for Eastern Europe and Latin America. This is mainly due to the high share of women from those regions working as domestic helpers and cleaners.

Contrary to conventional wisdom, the educational attainment is surprisingly high.[21] Considering the whole sample, more than 50% of the individuals has upper secondary education. One may think that highly educated people are over-represented in the sample because of a positive correlation between being educated and seeking health care. Indeed, this does not seem to be the case and, for instance, the percentage of university education is even higher in the Ismu estimates (see Devillanova and Frattini, 2006, Table 22). Table 3 provides more detailed information on schooling. Most immigrants from all regions possess at least high school education and, on average, women tend to be more educated than men. Figures for Eastern Europe are striking: 20.3% of women in the age bracket [25–64] have college education. Africa exhibits a high level of polarization, with a very large share of illiteracy (10.3% of North African men) and university education (12.1%). About 50% of individuals can speak Italian, with relevant differences across areas.

Unemployed people are probably over-represented in the sample for the reasons discussed in the previous section. Notwithstanding, their share appears dramatically high: 46% of the sample is unemployed, reaching almost two third for immigrants from Sub-Saharan Africa.[22] About 1.5% of immigrants are out of the labor force, half of which are

[21] Education is presumably acquired outside Italy. Actually, 76 individuals (0.76% of the sample) declare to be studying at the time of the interview. It is realistic to believe that some individuals may in fact be misreporting their unemployment status. This can be seen by observing that in Italy irregular immigrants are allowed in the school system only until 16, but 59 students in the sample are 17 or older, and 19 of them are in the age bracket [25–45].

[22] These figures contrast sharply with those on education. Notice, incidentally, that almost all employed immigrants perform elementary occupations in Italy, but about 15% of them were employed in elementary occupations in their country of origin; more than 5% were teachers or professors. It is important to bear in mind that dealing with information on occupation, both in the home country and in Italy, is a difficult task. The reason is that the interviewer asks an open question and some immigrants answer with their precise occupation, others just indicate the sector of activity. All the observations (3643 and 7794 observations for, respectively, the occupation in Italy and in the home country) have been processed manually and

students. The questionnaire distinguishes between permanent and temporary employment without providing a precise definition of the two categories. I suggest interpreting permanent employment as full time employment and temporary employment as any unstable sporadic occupation. Of course, being undocumented, none of the immigrants can have a claim to any legal employment protection legislation.

Finally, 83% of individuals came in contact with Naga through a strong social network (Section 3.1 defines and discusses the network indicator). The share of people with network equal to one is particularly high among immigrants from Asia and Latin America.

As a concluding remark, it is worth emphasizing that there is a great degree of heterogeneity across countries, even within a region, and between sexes, which is obscured by averages. Devillanova and Frattini (2006) provide more detailed information on the data, highlighting country and gender differences.

3. Empirical strategy

3.1. Information networks

In order to identify the role of information networks in influencing immigrants' access to health care, I exploit a specific question from the Naga interview that asks new patients to indicate who introduced them to the association. To do so, I construct a dummy variable (*network*) indicating if the Naga contact is a friend or a relative and I use this variable as a measure of the information network.

In the paper immigrants who became acquainted with Naga through a friend or a family member are often denoted as immigrants with a (strong social) network/contact/tie. This short label can be misleading, since I do not observe immigrants' actual social contacts. Obviously, I know for sure that immigrants with network equal to one do have at least one friend or relative in Italy. However, the opposite needs not to be true and people with network equal to zero may possess strong social contacts as well. To see this, consider the individuals who declared to reside with friends or kin: they certainly have a strong tie in Milan, but for 14.7% of them the network indicator is zero (for the rest of the sample the share of immigrants with network equal to zero is 23.2%).

Summing up, what I observe – and what is crucial in my analysis – is that those immigrants with network equal to one have relied on a friend or a relative in order to get the information on the health care services offered by Naga. At the same time, it must be acknowledged that the correlation between the network variable used in my analysis and an immigrant's actual social contacts is likely to be positive.

Notice that the identification of *strong ties* (friends and relatives), as opposed to *weak ties* (acquaintances), is fundamental in the sociological literature.[23] The former are more easily available and are often linked to economic insecurity and lack of social services.[24] For these reasons they are particularly important for poor people and are useful in explaining individuals' behavior with respect to welfare programs. Furthermore, the literature on migration chains and the settlement process in the host country has documented that recent cohorts of immigrants experience few weak ties and strongly rely on strong social contacts.[25] Strong contacts are usually associated with immigrants of the same nationality, although, unlike the studies that proxy the availability of networks with some measure of ethnic concentration, I do not need to make any further assumption hereof.

Actually, informal social relations may be even more important for undocumented immigrants. The reason for this is that illegal immigrants must minimize the probability of revealing their presence in Italy, in order to avoid deportation. The risk of detection noticeably limits the sources of formal information available to them.[26] Furthermore, since visiting Naga could itself be perceived as a risky action, strong social contacts may be crucial in

classified according to the European Union variant of the new International Standard Classification of Occupations (ISCO-88). The only occupation which can be unambiguously identified is "domestic helpers and cleaners", which is the focus of a companion paper.

[23] On the distinction between strong and weak social ties and their different utility in assistance versus social mobility see the seminal works of Granovetter (1973, 1983).

[24] For a discussion of this point, see Granovetter (1983), page 212, and references cited therein.

[25] See Massey (1986) and Winters et al. (2001). Bertrand et al. (2000) find that network effects are significantly stronger for foreign-born women who have recently entered the United States.

[26] Soenen and Soenen (2005) develop a model of job search strategy among undocumented immigrants which explicitly acknowledges that they cannot use formal job exchanges and where the risk of detection depends upon the dissemination of information.

fostering the belief that going to Naga and providing one's details has no direct consequences on the risk of being deported.

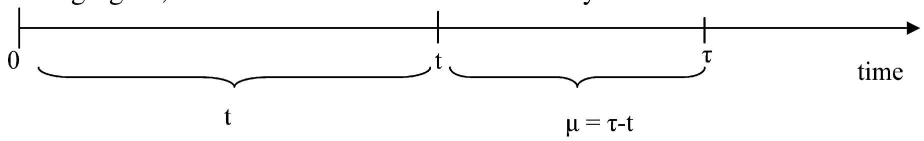
The previous consideration drives an important terminological clarification regarding the two possible channels (information and norms) through which networks operate. As a matter of fact, information is seldom neutral and social networks affect both the flow and the quality of information.[27] For instance, it is extremely likely that those providing information about the existence of Naga and its location also trust the service and encourage its use. The text emphasizes one aspect – the perceived risk of expulsion – which is distinctive of illegal immigration, but other features of the service as, for instance, its quality, are relevant as well. Here the crucial point is that the value judgments ingrained in information should not be confused with social norms. Norms always involve both a shared belief that persons ought or ought not to act in a certain way (a rule) and a mechanism of enforcement of the rule, with social sanctioning of deviance being a distinctive feature of the norm (Gibbs, 1965). In fact, the pervasiveness of norms and their enforcement are crucially linked to the network density (Granovetter, 2005). Furthermore, the literature on informal social relations among immigrants uses the term social norm in a narrow meaning, to denote the existence of ethnic attitudes. The following analysis controls for ethnic norms using country of origin fixed effects or other specific ethic attributes.

As a final remark, even if this measure of strong information network is far from being perfect, to the best of my knowledge this is the only study which can quantitatively address the question. At the same time, the usual attenuation bias caveat applies and, as long as the availability of an information network is imperfectly captured by the proposed indicator, the estimated network effect is biased toward zero.[28]

3.2. Access to health care

One peculiarity of the dataset is that immigrants are only observed if they approach Naga and therefore they all receive health assistance. For this reason I must study health care utilization by focusing on the time spent in Italy before the immigrant receives her/his first visit.

Consider the following figure, where 0 is the date of arrival in Italy and τ is the date of first visit at Naga.



In each time period, the individual has some positive probability of illness: t indicates the date at which the disease arrives and $E[t]$ is the expected healthy interval. At this point the immigrant needs health assistance and she/he decides whether or not to go to Naga: $E[\mu]$ denotes the expected time to visit. In principle, I would like to study how the information network affects μ – the time required to go to Naga conditional on needing health care – but I only observe τ – the time lag between date of arrival and date of first visit at Naga, whose expected length is $E(\tau)=E(t)+E(\mu)$. For instance, if the arrival rate of diseases and the arrival rate of information conditional on being sick[29] are both assumed to be Poisson with time invariant hazard rates γ_{ijn} and λ_{ijn}, respectively, then the average time to visit is $E(\tau_{ijn})=E(t_{ijn})+E(\mu_{ijn})=(1/\gamma_{ijn})+(1/\lambda_{ijn})$ where subscript i indicates the individual, j the country of origin and n is the availability of a network, making it clear that personal and ethnic characteristics and the availability of a network can affect both hazard rates.

Assume, for a moment, that the network indicator has no other consequence on the time to visit but the information effect addressed in this paper. If a strong social contact only provides information on Naga, it can hardly affect the healthy interval $E(t_{ijn})=E(t_{ij})$ and its correlation with $E(\tau_{ijn})$ has a straightforward interpretation. In particular, if friends and kin increase the flow of information and if this information is considered to be of better quality/more trustable than that obtained through other sources, it is reasonable to expect a shorter time to visit for immigrants who rely on a strong tie, relative to those who do not.

[27] Quoting Granovetter (2005), "much information is subtle, nuance and difficult to verify, so actors do not believe impersonal sources and instead rely on people they know", p. 33.
[28] See Aigner (1973).
[29] It is straightforward to allow for the arrival of information in the interval [0,t].

However, the above assumption is appropriate if all immigrants have the same opportunities to be referred to Naga by a strong social contact. It might be violated if, instead, the network indicator is correlated with the (unobservable) immigrants' actual social ties, since having friends or relatives in the same city can potentially affect the expected time to visit $E(\tau_{ijn})$ through other mechanisms besides the information effect.

The most obvious channel is the fact that relatives and friends can directly provide health assistance and monetary resources to the immigrant (I refer to this channel as aid). Presumably, aid increases both the expected healthy interval (since, by providing assistance, kin and friends are likely to improve the immigrant's health status) and the expected time to visit (the presence of strong social ties accommodates the immigrant with alternative resources, which could allow her/him to postpone or, as a limit case, to even prevent visiting Naga[30]). The crucial aspect of aid is that it should cause a positive bias of the coefficient of interest, hence reinforcing my identification strategy.[31] Nevertheless, one should be concerned about other channels which possibly work in the opposite direction, causing a negative correlation between the network indicator and the time to visit. For instance, friends and kin can affect the time to visit by persuading immigrants to use health care if in bad health conditions (shorter μ_{ijn}), or by inducing unhealthy behavior,[32] thus shortening t_{ijn}. Furthermore, individuals' social structure is to some extent endogenous and the presence of strong ties can be associated with unobservable individual characteristics negatively correlated with the time to visit.[33] In illustrating the regression results, in Section 4, I come back on these and other channels (besides the information network mechanism) through which the fact of having been presented to Naga through a friend or relative influences the time to visit. Section 4.4 explicitly addresses the distinction between norms and information.

3.3. Econometric specification

I regress the logarithm of the time to visit of individual i, from country j, on a constant, the network variable and a vector X_{ij} of individual and country specific controls:

$$\ln(\tau_{ij}) = \beta_0 + \beta_1 \text{network}_i + \beta_2' X_{ij} + u_{ij} \tag{1}$$

where $\tau_{ij} = (\text{date of first visit})_{ij} - (\text{date of arrival in Italy})_{ij}$ is the time to visit, in months, $\text{network}_i = 1$ if the Naga contact is a friend or a relative, and where no observation is censored by construction. None of the results of the paper depends on the log linear specification here used.[34]

Individual controls are all the available personal characteristics: knowledge of Italian, current employment, sex, age at entry in Italy, dummies for the number of cohabitants and for the number of children (alternatively, I use an indicator for having at least one child), education, a dummy for being married, accommodation, and occupation in the home country.[35]

Unfortunately, the dataset has no information on the reason for the visit and on the health status. I control for the health status using entry age in Italy, employment status and living conditions (accommodation and the number of cohabitants). The role of age is straightforward (Section 4.3 justifies the choice of controlling for age at entry rather then for age at visit and it shows that the results are robust to this choice). The employment status and the living conditions aim at capturing the immigrant's socioeconomic conditions in Italy, which can affect her/his health status.

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[30] For instance, households may provide health care at home, or they can lend money for a private visit.

[31] A related issue is that an individual can exit from the underlying population at any time, because, for instance, she/he moves away from Milan (clearly, I cannot observe this event). Relying on friends or relatives to get information on Naga can hardly have any effect on this outcome. If however the network indicator is positively correlated with actual social contacts, standard intuition is that immigrants with a strong social tie in Milan may be more likely to remain in the city, rather than to out-migrate. This too would cause a spurious positive correlation between the time to visit and the network indicator. Finally, notice that networks themselves may require time to be formed. I come back to this point in Section 4.3.

[32] McDonald and Kennedy (2005)'s analysis suggests that health-related behaviors, as diet and activity, are transmitted through social contacts.

[33] For instance, people that choose to move close to friends and kin may have a shorter μ_{ijn}, compared to individuals without a strong contact, because of unobservable characteristics of their personality. By a similar reasoning, as health care opportunities for illegal immigrants vary within Italy, it is possible that having a strong tie in Milan is particularly important for relatively less healthy immigrants, consequently shaping their location decision and causing a negative correlation between actual contacts and t_{ijn}.

[34] All the analysis has been replicated using a Cox proportional hazard model. Different parametric specifications of the duration model were also used, without affecting any of the results.

[35] Occupations are classified in 11 categories, as detailed in Table 4. See also footnote 22 and Devillanova and Frattini (2006).

Notice, anyhow, that in principle most individual traits included in the analysis can capture some of the unobserved heterogeneity in health that will in part determine duration until health care is sought.

Sex, education, occupation at home, marital status and number of children are mainly intended to control for the immigrant's attitude towards health care. In particular, education and employment characteristics at home could reflect previous socio-economic status and so proxy for general attitudes toward health behavior.

As for the knowledge of Italian, it can clearly affect the time required to access Naga, because, for instance, immigrants can ask for information, read advertisements, etc. Notice however that both the knowledge of Italian and the employment status are potentially endogenous variables, as the time spent in Italy is likely to affect the probability of being employed and the probability of having learnt the language. I include them in the analysis since they bias the network effect toward zero, making it less likely that I find a negative effect.

Country of origin controls are a set of country fixed effects, which aim at capturing country heterogeneity and, in particular, possible ethnic attitudes towards health behavior. Table 10 replaces country fixed effects with specific attributes of the ethnic community.

4. Results

4.1. Preliminary inspection

The first two columns of Table 4 report, by network, mean, standard deviation and number of available observations of the variables used in the following regression analysis. The sample differs from the one used in the descriptive analysis of Section 2, in that it is restricted to non-missing observations for the date of birth, education and employment status in Italy and to countries with more than 26 observations.[36] After imposing these restrictions, we are left with 8700 non-missing observations for the network indicator, implying a loss of 8% of the sample. I will address the consequences of these choices in the robustness checks of Section 4.3. The network dummy is equal to one for 84% of the sample.

A preliminary inspection of the descriptive statistics highlights that the time to visit tends to be substantially shorter for immigrants who received information through a strong social contact: the time to visit for immigrants with and without network is, respectively, 16.3 and 24.4 months. The picture is similar if one looks at the median values (9.6 and 14.4, respectively).

Fig. 1 illustrates this fact by plotting the Kaplan–Meier survival estimates and the hazard rates: in the first 50 months after arrival, the hazard rate is constantly higher for individuals with a network compared to individuals without a network. The figure only looks at spells shorter than 100 months; afterwards the two curves are more erratic. Notice, however, that only very few observations have a time to visit longer than 2 years (see Fig. 2).

These crude facts already suggest that immigrants relying on friends and relatives in order to access Naga may have a shorter time to visit. However, before one can draw any conclusion on the network effect, controls must be added.

Table 4 also presents summary statistics for the 627 observations for which the network is missing. Looking at the time to visit suggests that on average immigrants with missing information on the network resemble those with network equal to zero. This sounds plausible as long as a vague answer to the question on the Naga contact, which is likely to be recorded as missing, is more frequent among contacts other than family and friends. The subsequent analysis, except column 2 of Table 6, is carried out omitting records for which the network indicator is missing.

4.2. Main results

Table 5 presents estimates of model (1). Columns differ from each other in the number of controls included.[37] In all cases, robust standard errors are adjusted for clustering at the country level.

The main results of the paper are reported in the last column 7, which includes all the available individual controls and country fixed effects. Two findings are worth emphasizing.

[36] The date of birth is important as it allows controlling for age; education and employment are core variables in addressing the information content of the network indicator (see Section 4.4).

[37] Unless otherwise specified, missing observations for cohabitants, married, housing and occupation at home have been coded as additional categories. Table 6 addresses the consequences of this choice on the estimated network effect. In an early working paper version all the analysis is carried out using complete records only.

Table 4
Summary statistics for the regression sample

	Network = 0			Network = 1			Missing network		
	Mean	S.D.	Number of observations	Mean	S.D.	Number of observations	Mean	S.D.	Number of observations
Time to visit (months)	24.38	30.46	1380	16.32	22.67	7320	23.65	35.16	627
Man	0.63	0.48	1380	0.55	0.50	7320	0.62	0.49	627
Age at migration (years)	29.39	9.10	1380	30.46	9.26	7320	30.99	9.34	627
Education									
No education	0.04	0.19	1380	0.03	0.17	7320	0.04	0.19	627
Primary	0.10	0.30	1380	0.10	0.30	7320	0.11	0.31	627
Secondary	0.35	0.48	1380	0.35	0.48	7320	0.35	0.48	627
High	0.41	0.49	1380	0.42	0.49	7320	0.42	0.49	627
University	0.10	0.31	1380	0.10	0.30	7320	0.10	0.29	627
Italian	0.60	0.49	1380	0.51	0.50	7320	0.45	0.50	627
Out of labor force	0.02	0.15	1380	0.01	0.11	7320	0.01	0.11	627
Unemployed	0.39	0.49	1380	0.47	0.50	7320	0.45	0.50	627
Permanent employment	0.31	0.46	1380	0.26	0.44	7320	0.28	0.45	627
Temporary employment	0.28	0.45	1380	0.26	0.44	7320	0.25	0.43	627
Married	0.43	0.50	1359	0.47	0.50	7251	0.47	0.50	612
Single	0.52	0.50	1359	0.47	0.50	7251	0.45	0.50	612
% with children (parent)	0.46	0.50	1380	0.49	0.50	7320	0.46	0.50	627
Number of children	1.05	1.48	1380	1.13	1.51	7320	1.02	1.43	627
Number of cohabitants	4.15	2.34	1050	4.38	2.10	6251	4.24	2.16	430
Accommodation									
Other	0.14	0.35	1250	0.06	0.23	6595	0.13	0.33	569
Employer	0.07	0.26	1250	0.06	0.24	6595	0.07	0.26	569
Friends/relatives	0.70	0.46	1250	0.79	0.41	6595	0.65	0.48	569
Own	0.08	0.27	1250	0.09	0.29	6595	0.16	0.36	569
Profession at home									
Out of labor force	0.06	0.23	1066	0.07	0.26	5749	0.07	0.25	462
Unemployed	0.08	0.27	1066	0.05	0.22	5749	0.07	0.25	462
Other	0.01	0.07	1066	0.01	0.07	5749	0.00	0.07	462
Professionals	0.08	0.27	1066	0.07	0.26	5749	0.08	0.26	462
Tech. and associate	0.06	0.24	1066	0.06	0.25	5749	0.06	0.25	462
Clerks	0.08	0.27	1066	0.09	0.29	5749	0.10	0.30	462
Service and shop	0.16	0.37	1066	0.19	0.39	5749	0.17	0.37	462
Craft and related	0.13	0.34	1066	0.12	0.32	5749	0.12	0.32	462
Plant and machine	0.04	0.20	1066	0.05	0.22	5749	0.05	0.22	462
Elementary	0.17	0.37	1066	0.16	0.37	5749	0.17	0.38	462
Students	0.14	0.35	1066	0.13	0.33	5749	0.11	0.32	462
Eastern Europe	0.26	0.44	1380	0.13	0.34	7320	0.18	0.38	627
Asia	0.08	0.27	1380	0.13	0.34	7320	0.14	0.35	627
North Africa	0.27	0.44	1380	0.18	0.38	7320	0.22	0.41	627
Sub-Saharan Africa	0.09	0.28	1380	0.07	0.25	7320	0.07	0.26	627
Latin America	0.31	0.46	1380	0.50	0.50	7320	0.39	0.49	627

The sample is restricted to non-missing observations for the date of birth, education and employment status in Italy, and to countries with more than 26 observations.

First, the network indicator has a negative effect on the time required to access Naga, significant at the 1% level.

Second, this effect is quantitatively important: relying on a strong social tie reduces the time to visit by around 28.5%. This implies that, on average, being referred by one's network decreases the predicted time to visit by 5.1 months. For the purpose of comparison, notice that the predicted difference between an unemployed immigrant relative to an immigrant with a temporary job is 5.4 months; having no education as compared to secondary education increases the predicted time to visit by 4.3 months, with no significant advantage of having high school or university education.

Table 5
Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Network	−0.479*** (0.059)	−0.405*** (0.047)	−0.297*** (0.040)	−0.289*** (0.037)	−0.283*** (0.036)	−0.286*** (0.036)	−0.285*** (0.035)
No active			−0.337*** (0.118)	−0.332*** (0.116)	−0.310*** (0.110)	−0.315*** (0.110)	−0.303*** (0.105)
Unemployed			−0.561*** (0.074)	−0.554*** (0.074)	−0.555*** (0.075)	−0.548*** (0.076)	−0.546*** (0.075)
Permanent employ			0.262*** (0.031)	0.261*** (0.030)	0.247*** (0.033)	0.234*** (0.032)	0.235*** (0.032)
Italian			0.550*** (0.037)	0.540*** (0.034)	0.540*** (0.034)	0.564*** (0.034)	0.564*** (0.035)
Man				−0.014 (0.038)	−0.006 (0.037)	0.004 (0.037)	−0.001 (0.041)
No education				0.404***[0.108)	0.419*** (0.103)	0.410*** (0.105)	0.401*** (0.106)
Primary				0.122*** (0.059)	0.127** (0.060)	0.118* (0.061)	0.120* (0.061)
High school				−0.016 (0.033)	−0.011 (0.032)	−0.042 (0.032)	−0.051 (0.035)
University				0.043 (0.053)	0.052 (0.051)	0.034 (0.052)	0.021 (0.055)
Age at migration				−0.016*** (0.005)	−0.016*** (0.005)	−0.016*** (0.005)	−0.016*** (0.005)
Parent				0.178** (0.081)			
Number of children					Y	Y	Y
Number of cohabitants					Y	Y	Y
Married					Y	Y	Y
Accommodation						Y	Y
Profession at home							Y
Country dummies		Y	Y	Y	Y	Y	Y
Constant	Y	Y	Y	Y	Y	Y	Y
Observations	8700	8700	8700	8700	8700	8700	8700
R^2	0.02	0.09	0.24	0.25	0.26	0.26	0.26

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.
The excluded level of education is secondary education. For the employment status, the excluded category is temporary employment.

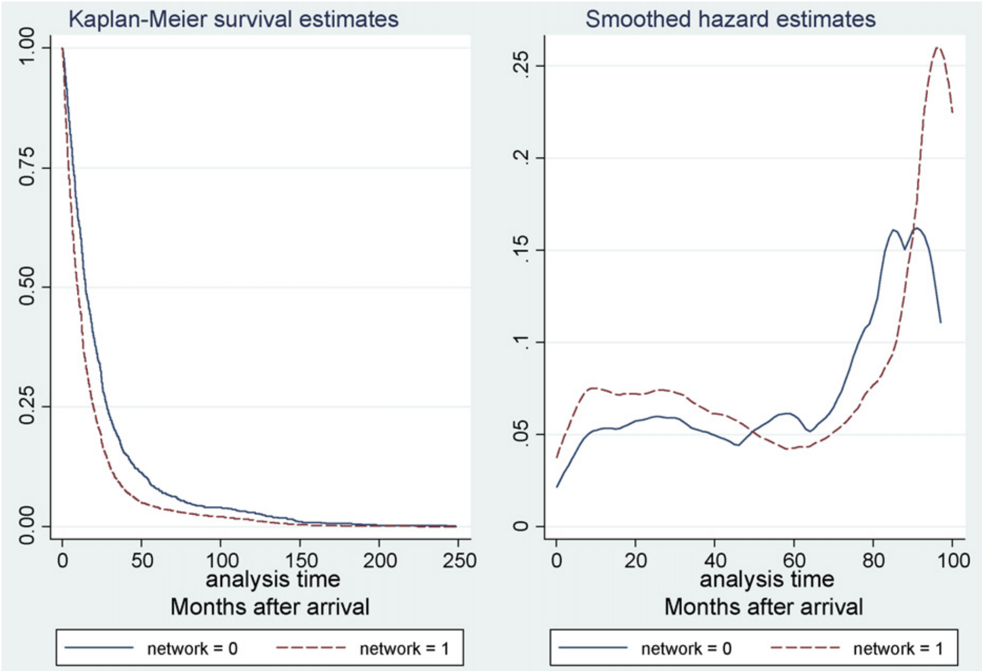

Fig. 1. Survival and hazard rates, by network.

In general, it would be informative to contrast the network effect with those of the other individual controls, which might be of some independent interest. However, the role of most regressors should be interpreted with caution because of the low quality of some variables and of possible sample selection. For instance, more educated people are more likely to exit the pool of undocumented migrants, either because they are successful in getting a legal permit or because they migrate abroad. This could bias the related coefficients downwards, actually reinforcing the importance of networks compared to education. Similar considerations apply to the employment status (see also Section 2.2). Gender has no significant effect; having at least one child is associated with a longer time to visit. As expected, the older the age of immigration the shorter the time to visit. I also checked for non-linear specification in age. Results, not reported, show that the dummies for the number of children and for cohabitants are significant and get larger, in absolute value, as the number of offspring increases; the coefficients on accommodation and on marital status indicators are not statistically different from zero. I also explored whether the network effect varies with age, by interacting the age at migration with the network dummy. The estimate coefficient on the network dummy is −0.556 (standard error 0.125), age at migration

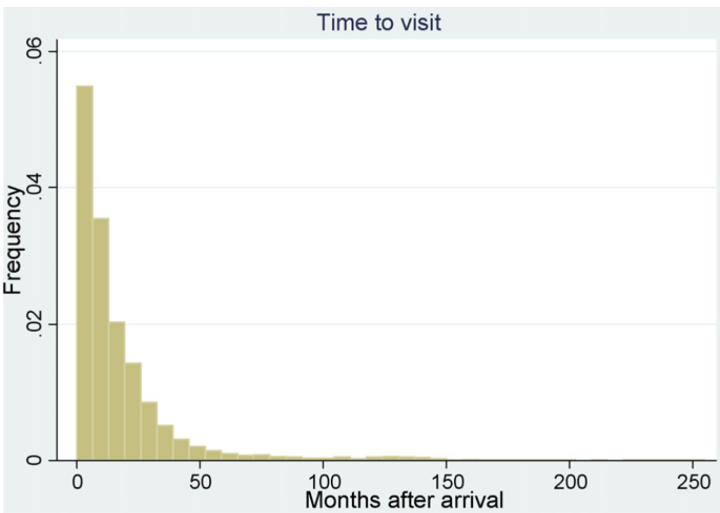

Fig. 2. Frequency of the time to visit.

is −0.024 (standard error 0.006), and the interaction term is 0.009 (standard error 0.004). This result could be due to the correlation between heath status and age. In fact, if we assume that younger people are more likely to be in good health, this suggests that for healthier immigrants the information provided by friends and relatives is relatively more important in shaping their decision to go to Naga.[38] In the next two sections, I provide further details on the role of other individual controls and interaction terms.

Finally, it is important to highlight that the network effect is fairly stable across specifications 3–7 of Table 5. This point is worth commenting on. One major caveat of the present analysis concerns the potential correlation between the network indicator and the (unobservable) immigrants' actual social ties. As discussed in Section 3.2, this possibility is challenging for the interpretation of the results. The expected time to visit could in fact be shorter for people with network equal to one because of unobservable characteristics[39] correlated with the network indicator, which have nothing to do with the information effect addressed in this paper. Table 5 indirectly addresses the problem[40]: I follow Bertrand et al. (2000)'s argument and I argue that if this were the case, treating observable characteristics as unobservable should have a large impact on the estimate of the network effect. In particular, in column 1 the logarithm of the time to visit is regressed on the network variable and on a constant. Column 2 adds country fixed effects and the estimated coefficient of the network drops, in absolute value, by about 15%. Column 3 controls for the possibly endogenous knowledge of Italian and employment status in Italy, and again the point estimate of the network effect drops by another 23%. Column 4 includes sex, education, age and a dummy, parent, equal to 1 if the immigrant has at least one child. The point estimate of the network effect changes only marginally. In column 5 I substitute parent with a full set of dummies for the number of children. I also control for the number of cohabitants and for being married. Column 6 further controls for accommodation. Finally, column 7 includes the occupation in the home country. This specification is going to be used in the rest of the paper and it will be referred to as the baseline specification.

The estimate of the network effect is stable across specifications and is unaffected by the inclusion of additional individual controls. Under the plausible assumption that the individual unobservable attributes discussed at the end of Section 3.2 are correlated with observables like sex, age, education, accommodation, occupation at home, this result suggests that the estimated network effect is unlikely to be the consequence of pure unobservable characteristics. In turn, this can either be due to the fact that the mechanisms that could bias the network effect are empirically of minor importance, or to the fact that there is low correlation between the actual social contacts and the network indicator.

4.3. Robustness checks

Table 6 presents some robustness checks. To facilitate comparisons, column 1 reports the baseline specification (column 7 of previous table).

In column 2, missing observations for the network indicator, education and employment have been coded as additional categories, gaining an additional 1137 observations. The estimate of the network effect is 0.7% lower (it is −0.274 if only the 392 missing observations for education and employment are included). Notice, incidentally, that the dummy for the missing network indicator (not reported in the table) is not statistically different from zero (point estimate −0.089, standard error 0.057), supporting the intuition that the Naga contact is more often recorded as missing for immigrants with network equal to zero.

Column 3, conversely, restricts the analysis to complete records only: 3125 observations are lost due to missing observations on some individual control. The point estimate of the network effect is larger in absolute value but so is the standard error.

Next, I check if the results are driven by the choice of limiting the analysis to countries with more than 26 observations. Indeed, they are not. Columns 4 and 5 look at countries with more than 200 and 2 observations, respectively.

[38] It can also indicate that younger people more heavily confide in information obtained through friends and relatives. I have also checked whether the network effect varies with marital status, but the interaction term is not statistically different from zero.

[39] I checked for possible selection on observables and I found no evidence of it. In particular, I regressed the time to visit for those immigrants who have network equal one on the hazard rate of having a network, controlling for personal and country characteristics. The estimated coefficient is positive but never different from zero at any level of significance.

[40] A more satisfactory solution of the problem would have been to instrument the network indicator. Unfortunately, none of the available individual characteristic is a credible instrument. Neither is it convincing to instrument the network indicator using ethnic attributes, as it precludes the possibility of controlling for the important country of origin heterogeneity.

Table 6
Robustness checks

	(1) Baseline	(2) Missing included	(3) Complete records	(4) Population > 200	(5) Population > 2
Network	−0.285*** (0.035)	−0.278*** (0.033)	−0.328*** (0.044)	−0.292*** (0.038)	−0.277*** (0.033)
Constant	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y
Observations	8700	9837	5575	7257	9005
R^2	0.26	0.26	0.27	0.26	0.26

	(6) Women	(7) Men	(8) Age at visit	(9) Age visit [15–45]	(10) Age visit [25–45]
Network	−0.234*** (0.044)	−0.310*** (0.040)	−0.297*** (0.037)	−0.275*** (0.037)	−0.222*** (0.043)
Constant	Y	Y	Y	Y	Y
Individual controls	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y
Observations	3772	4928	8700	7905	5713
R^2	0.26	0.27	0.26	0.26	0.30

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.
Column 1 reports the baseline regression. In column 2, missing observations for the network indicator, education and employment have been coded as additional categories. Column 3 is restricted to individuals with complete records. Columns 4 and 5 include countries with more than 200 and 2 observations, respectively (all the other regressions in the paper looks at countries with population >26). Columns 6 and 7 estimate the model separately for women and men, respectively. Column 8 replaces age at entry in Italy with age at visit. Column 9 is restricted to those individuals younger than 45; column 10 further excludes individuals below age 25.

Table 5 reveals that gender does not have a direct impact on the time to visit. Columns 6 and 7 of Table 6 estimate the model separately for, women and men, respectively. The network effect is stronger for men than for women, but the difference is not statistically significant at the 10% level. This conclusion is analogous if I include the interaction of network with gender in the baseline regression (the interaction term is −0.085, standard error 0.054).

The last three columns focus on the age at visit. In column 8, age at entry has been replaced by age at visit. As the results show, the effect of network is – if anything – stronger when I control for age at visit rather than age at entry. Although age at visit is arguably a better indicator of the health status of the individual, in this model I think it is more appropriate to control for age at entry. Age at visit is simply the sum of age at entry and time to visit, and the log of time to visit is the dependent variable of the analysis; so when I control for age at visit I am still mainly exploiting variation in age at entry. Since, for the same reason, it is not possible to control for age at visit and age at migration simultaneously, column 9 omits people older than 45; column 10 omits those below age 25 and over 45.[41]

4.4. *Further investigations*

This section aims at more closely exploring the possible channels through which the network indicator correlates to the time to visit.

Table 7 looks at the alternative sources of information, by disaggregating the network indicator in subcategories. Concerning the 7320 individuals who have received information through a strong network, for 17.5% of them the network is a relative, for the remaining 82.5% it is a friend. Most immigrants with no network came in contact with Naga through public hospitals (about 73% of them). The remaining 27% knew Naga though either religious associations (5.2%) or other heterogeneous sources of information (21.8%).

Column 1 of Table 7 distinguishes between relatives and friends. The estimated network effect for relatives is two times that for friends. This result can be explained by noting that family networks are, indeed, immediately available to the immigrant (and immediately trustable), while friendships may require time to be strengthened. This should introduce a spurious positive correlation between relying on friends to get information and the time to visit, biasing

[41] Notice that, by omitting people younger than 25, I reduce the possibility of having immigrants who could have acquired education in Italy. I also addressed this issue by omitting from the analysis both students and individuals whose age at migration is less than 25.

Table 7
Time to visit and alternative sources of information

	(1)	(2)	(3)
Naga contact			
Network = 1 (friends/relatives)		−0.322*** (0.037)	
Relatives	−0.523*** (0.081)		−0.560*** (0.073)
Friends	−0.239*** (0.034)		−0.277*** (0.039)
Religious associations		−0.137 (0.129)	−0.142 (0.126)
Other sources of information		−0.142 (0.088)	−0.140 (0.088)
Constant	Y	Y	Y
Individual controls	Y	Y	Y
Country dummies	Y	Y	Y
Observations	8700	8700	8700
R^2	0.27	0.26	0.27

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.
In columns 2 and 3 the excluded category for the Naga contact is hospitals/doctors.

the network coefficient toward zero. A second possible reason is that the measurement errors in the network indicator might be more frequent for friends than for relatives. Indeed, the term friend can be also used in a loose sense to indicate simply someone who offered help, while the term relatives has a much more precise meaning.

Column 2 identifies, within the set of immigrants with network equal to zero, those who got in contact with Naga through religious associations, hospitals/doctors and the residual category other sources of information (the excluded category is hospitals/doctors). Both religious associations and other sources of information have a negative impact on the time to visit, although it is not statistically significant. Remarkably, the estimated network effect increases in absolute value to 0.322. I obtain the same result if I restrict the analysis to those individuals who came in contact with Naga through hospitals/doctors. These findings can be explained by noting that religious associations (and, to some extent, some of the residual sources of information) are, indeed, different types of social networks, which might facilitate the access to information as well. In this respect, the choice of including them in the analysis is conservative. Column 3 presents the unrestricted specification, which distinguishes between all the alternative sources of information.[42]

One concern of the present analysis, which has already been indirectly addressed in Table 5, is that the network indicator may capture the effect on the time to visit of having friends and kin in Milan, rather than a flow of information. Table 8 takes up the issue again, by looking more closely at the role of living conditions. Previous specifications include dummies for accommodation and for the number of cohabitants, in order to control for some of the unobserved heterogeneity in health. However, these variables are also likely to capture immigrants' actual social contacts. In particular, by construction the cohabitation variable for living with friends/relatives indicates the presence of a strong social contact in Milan. On the other hand, the number of cohabiters (friends in a loose sense) could proxy for the dimension of the immigrant's actual social network, which is surely a relevant aspect for the working of the network itself. Therefore, if the previous results are mainly driven by the correlation between the network indicator and the actual social contacts, I should also find a negative and significant effect of each cohabitation variable.

Column 1 estimates the network effect excluding these two variables from the set of controls. The analysis is restricted to records with complete information on accommodation and number of cohabitants (there are 6553 available observations). Columns 2 and 3 replace the network indicator with, respectively, living with friends/relatives and the number of cohabitants. Column 4 includes all the three variables. Column 5 adds their interactions, as the network effect may vary according to the availability of contacts (for instance, by providing aid, kin reduce the importance of information) and the health status (as already mentioned, information could be relatively more effective in shaping the healthier individuals' decision to go to Naga).

[42] This specification has been used to replicate all the regressions of the paper. The analysis does not provide any additional insight with respect to what is reported here.

Table 8
Time to visit and cohabitation

	(1)	(2)	(3)	(4)	(5)
Network	−0.320*** (0.037)			−0.320*** (0.037)	−0.283** (0.103)
Living with friends/relatives		−0.059 (0.043)		−0.051 (0.046)	0.095 (0.076)
Number of cohabitants			−0.024*** (0.007)	−0.024*** (0.007)	−0.046*** (0.012)
Network × living with friends/relatives					−0.169* (0.086)
Network × number of cohabitants					0.027** (0.010)
Constant	Y	Y	Y	Y	Y
Other individual controls	Y	Y	Y	Y	Y
Country dummies	Y	Y	Y	Y	Y
Observations	6553	6553	6553	6553	6553
R^2	0.27	0.26	0.26	0.27	0.27

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.
All the regressions are restricted to individuals with non-missing observations for housing and number of cohabitants.

Results show both that living with friends/relatives and the number of cohabitants have a negative effect on the time to visit, but only the latter is statistically significant, with 1 standard deviation increase in the number of cohabitants yielding to a 0.04 standard deviation decrease in the logarithm of the time to visit. The network effect is smaller the larger is the number of cohabitants. Conversely, the interaction of the network indicator with the cohabitation variable for living with friends/relatives is negative and only marginally significant. These results suggest that the two cohabitation variables are capturing different mechanisms and are consistent with the hypothesis that the number of cohabitants better proxies for the immigrant's socio-economic condition. More cohabitants should therefore be associated to worse living conditions and, consequently, to a higher probability of disease and a shorter time to visit.

Finally, notice that the inclusion of the cohabitation variables has no effect on the point estimate of the network indicator. Overall, these findings reinforce the conclusion that the network indicator is identifying something else besides the mere presence of strong social ties in Milan.[43] The next two tables try to further explore whether it is capturing information.

The network indicator is equal to one if the immigrant became acquainted with Naga through a friend or kin. This definition induces us to interpret its effect as evidence of the information mechanism through which networks operate. However, one might conjecture that those who recommend the use of Naga to others also exert some form of social pressure, which persuades people to go to Naga. In this case, the network indicator could therefore be identifying social norms as well.

Column 1 of Table 9 checks whether the network effect differs across education levels. Suppose that information is the mechanism though which the networks operate. As such, one would imagine that those for whom information is harder to come by would benefit more from additional information. If those with less education could benefit more from information, we should expect that having a network should matter more for them. The idea is that the level of education is correlated with the immigrant's ability to learn foreign languages, to understand institutional details and, in general, to exploit different information channels. Less educated immigrants should therefore find it difficult to access alternative sources of information and more heavily rely on strong networks. To test this, I interact the network variable with the education dummies (the excluded category is secondary education).

Column 1 first shows that the education dummies reveal a relative advantage of educated immigrants in reaching Naga (incidentally, the coefficients on the education dummies acquire significance once interactions are included). This result could be shaped by the potential correlation between education and the immigrant behavior, with more education associated to greater propensity to use health care. Notice, however, that as observed in Section 2.2, the

[43] A related concern is that friends and relatives might themselves be a transmission mechanism of contagious diseases, thus reducing the expected time to visit. In order to explore this possibility, I interact the network with seasonal dummies. The idea is that if the epidemic effect is important, I should observe a stronger negative coefficient of the network indicator in periods of high frequency of contagious diseases—typically flu at the beginning of the cold season. I try several different specifications, with monthly dummies and different seasonal dummies, but I do not find such an effect.

Table 9
Interactions with education, Italian and being employed

	(1)		(2)	(3)
Network	−0.338*** (0.055)	Network	−0.335*** (0.055)	−0.498*** (0.092)
No education × network	−0.116 (0.144)	(No education and primary) × network	−0.207*** (0.071)	−0.181** (0.074)
Primary × network	−0.222** (0.092)	(High and university) × network	0.152** (0.070)	0.133* (0.072)
High × network	0.118 (0.076)	Italian × network		0.009 (0.061)
University × network	0.294*** (0.096)	Worker × network		0.269*** (0.077)
No education	0.493*** (0.137)	No education and primary	0.354*** (0.101)	0.332*** (0.104)
Primary	0.305** (0.113)	High and university	−0.167*** (0.057)	−0.149** (0.059)
High	−0.151** (0.057)	Italian		0.561*** (0.062)
University	−0.228** (0.107)	Worker		0.417*** (0.089)
Constant	Y	Constant	Y	Y
Individual controls	Y	Individual controls	Y	Y
Country dummies	Y	Country dummies	Y	Y
Observations	8700	Observations	8700	8700
R^2	0.26	R^2	0.26	0.26

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.
For schooling, the excluded category is secondary education. In column 2 and 3 no education is grouped with elementary education and high school with university; worker is a dummy equal to one if the immigrant has either a temporary or a fixed job and it replaces the four dummies for the employment status in the individual controls.

comparison between the educational attainments in the Naga sample and Ismu estimates does not provide evidence of a positive correlation between being educated and seeking health care.

Second, the network effect decreases with the level of education. For instance, on average having received information on Naga through a strong network reduces the time to visit of an immigrant with primary education by 56%. The effect is much lower (around 4%) for immigrants with university education. The picture is similar in column 2, where education levels have been grouped into three categories: no education and primary education; secondary education; high school and college education (as before, the excluded category is secondary education).

By the same token, in column 3, the network variable is interacted with the (grouped) education dummies, the Italian dummy and a worker dummy equal to one if the immigrant is employed (either temporary or fixed employment), which substitute for the employment status in the individual controls. In fact, although the knowledge of Italian and the employment status are potentially endogenous variables, they both facilitate the acquisition of information and, consequently, they should reduce the value of information networks. In particular, workers are more likely to be exposed to contacts outside their immediate social group and to acquire more channels of information.

Results show that the interaction network-worker is positive and highly significant. The stronger effect of the network indicator for less educated people is also confirmed, although the inclusion of the additional interaction terms reduces the statistical significance of the related terms. The interaction of the network indicator with the Italian dummy turns out to never be statistically significant, regardless of the number of individual controls included. In my opinion, the differential effect of the network indicator across educational categories and between employed and unemployed people provides support for the information channel hypothesis addressed in this paper.

Previous regression analysis controls for possible ethnic norms by including the country of origin fixed effect. Table 10 addresses the source of country heterogeneity, by substituting country fixed effects with four attributes of the ethnic community. First, I control for the country average time to visit (the average is computed excluding individual i), which aims at capturing cultural factors, as, for instance, trust in western medicine, which may induce some ethnic group to more promptly use health services offered by Naga. It can be linked to the *quality* of the ethnic community. Second, I include the ratio between the number of observations from country j in the sample and the number of undocumented immigrants from the same country of origin, according to Ismu estimates (see footnotes 18 and 20). This ratio aims at controlling for differences in the probability of using Naga services between communities. Third, I add the country share of regular immigrants in Milan–Ismu, 2001. This is a measure of ethnic concentration, which is usually used to proxy for *contact availability*. Finally, I use a measure of the degree of ethnic cohesion,

Table 10
Time to visit and ethnic attributes

	(1)	(2)	(3)
Network	−0.306*** (0.034)	−0.309*** (0.035)	−0.304*** (0.034)
Mean lag		0.905*** (0.069)	0.644*** (0.075)
Ratio		−0.086*** (0.030)	−0.075*** (0.017)
re_ismu		−1.084*** (0.337)	−1.418*** (0.361)
% Network = 1		0.809** (0.290)	0.229 (0.272)
Constant	Y	Y	Y
Individual controls	Y	Y	Y
Country dummies	Y		
Area dummies			Y
Observations	8205	8205	8205
R^2	0.26	0.25	0.26

Robust standard errors in parentheses. Standard errors have been adjusted for clustering at the country level. *Significant at 10%; **significant at 5%; ***significant at 1%.

All the regressions are restricted to countries with population >26. Column 1 replicates the baseline regression of Table 5, column 7, excluding countries for which the Ismu estimates are not available. Country attributes are: mean lag = average time to visit of immigrants from country j (the average is computed excluding individual i); ratio = number of observations from country j in the sample divided by the number of undocumented immigrants from country j according to Ismu estimates (see footnotes 18 and 20); re_ismu = share of legal immigrants from country j in the Ismu estimates; % Network = 1 is the share of immigrants from country j with network equal to one.

defined as the share of immigrants from country j with network equal to one. Here the idea is that if the network indicator brings social norms beside information, the percentage of people who have been advised to use Naga services should capture both the ethnic community's general evaluation of Naga as well as the degree of social pressure in the community. The higher the cohesion, the more pervasive the ethnic norm and the stronger its enforcement, the shorter the time to visit. Of course, the estimated coefficients on these four variables do not allow inferring any causal relationship.

Column 1 of Table 10 replicates the baseline specification, where the sample is now restricted to those countries for which the Ismu estimates are available. The point estimate of the network effect is slightly higher. This can be partly due to the exclusion of immigrants form Ukraine, who have an extremely high level of education, since the network indicator has been shown to be more important for less educated people. In column 2, the country fixed effect has been replaced with the country controls presented above and in column 3, five area dummies for the region of origin are included.

Two results are worth emphasizing. First, the average time to visit, the ratio Naga/Ismu of irregular presences and the share of regular immigrants all have the expected sign. Second, the estimated coefficient on the ethic cohesion is positive and not significant at standard levels. This latter result is very robust to the inclusion of individual and country controls. I have also looked at the interaction between the average time to visit and the share of immigrants with network equal to one, and no significant effect emerges. This finding supports the idea that the network indicator used in this paper does not act as a transmission mechanism for social norms among individuals of the same nationality (it can not rule out social norms if the immigrant's reference group is not defined on ethnicity) and it reinforces the intuition that the analysis is mainly capturing the information channels.

5. Conclusions

This paper addresses the effects of social networks as an information device in shaping undocumented immigrants' access to health care. As Borjas and Sueyoshy (1997) acknowledge, assessing the consequences of alternative policy proposals requires a much deeper understanding of the channels through which ethnic networks operate. Unfortunately, the relative importance of these channels (specifically information and norms) has hardly been addressed in previous quantitative research.

This study can be considered as a step in this direction. The data I use report whether an individual has become aware of health care opportunities through a friend or a relative. This allows focusing on the information channel involved in strong social ties.

Results show that relying on friends and kin in order to get information on Naga significantly accelerates health care utilization, reducing the time to visit by about 30%. The effect of the network indicator is stable across specifications and is particularly strong for less educated individuals.

As a concluding remark, it is important to bear in mind that the present analysis is subject to a few caveats. In particular, analyzing data on undocumented immigrants limits the generality of the results. At the same time, however, this study sheds some light on this hidden yet important phenomenon.

These findings can have direct policy implications. Policies aimed at increasing the use of primary health care by immigrants or minorities can exploit the multiplier effect of information networks. For instance, the program could be advertised in immigrants' meeting areas and newspapers, providing the related information in different foreign languages. In general, knowledge of the working of social networks could help in addressing ethnic differences in take-up rates and immigrants' welfare assimilation processes, coping with racial segregation and vicious circles of welfare dependency/exclusion.

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Appendix A. Definition of regions

- *Europe*: Albania, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, Hungary, Former Jugoslavia, Kosovo, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia and Ukraine.
- *Asia*: Armenia, Bangladesh, Chechnya, China, Georgia, India, Indonesia, Iran, Iraq, Jordan, South Korea, Kurdistan, Lebanon, Myanmar, Nepal, Pakistan, Palestine, Philippines, Sri Lanka, Syria, Thailand, Turkey and Yemen.
- *North Africa*: Algeria, Egypt, Libya, Morocco and Tunisia.
- *Sub-Saharan Africa*: Angola, Benin, Burkina Faso, Burundi, Cameroons, Congo, Eritrea, Ethiopia, Gambia, Ghana, Guinea, Guinea Bissau, Ivory Coast, Kenya, Madagascar, Mauritania, Mauritius, Niger, Nigeria, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Uganda, Zaire and Zambia.
- *Latin America*: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Ecuador, El Salvador, Dominican Republic, Guatemala, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay and Venezuela.

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