Document Title: Police Innovations and the Structure of Informal Communication Between Police Agencies: Network and LEMAS Data

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Document No.: 216150

Date Received: November 2006

Award Number: 2003-IJ-CX-1002

FINAL REPORT

NIJ Grant #2003-IJ-CX-1002

Police Innovations and the Structure of Informal Communication Between Police Agencies: Network and LEMAS Data

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September, 2006

Points of view in this document are those of the authors and do not necessarily represent the official position or policies of the U.S. Department of Justice. We thank Brett Chapman of the National Institute of Justice for his kind and generous help in the management of the grant. Anonymous reviewers of the draft report and associated journal submissions made helpful comments. Devon Brewer also made many valuable comments on one associated journal submission. Part of this research was presented at the annual meeting of the International Network for Social Network Analysis, Redondo Beach, CA, February, 2005. Part of this report expands on some material from the article “The Structure of Informal Communication Between Police Agencies”, (forthcoming), by A. Roberts and J. M. Roberts, Jr., in *Policing: An International Journal of Police Strategies and Management* (copyright Emerald Group Publishing Limited).

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Abstract

This study examined (i) the pattern of informal communication ties between police agencies and (ii) the influence of network contacts on adoption of innovations and change in agency practices. To study the structure of the police network, we used Weiss' (1997a) data set, Communication of Innovation in Policing in the United States (ICPSR #2480), on informal contacts between police planners at different city, county and state police agencies. We then also used the network data in models to predict adoption of or change in agency practices as indicated in the Law Enforcement Management and Administrative Statistics (LEMAS) data sets for 1997, 1999 and 2000 (ICPSR #2700, #3079 and #3565), with some supplementary data drawn from the Census of State and Local Law Enforcement Agencies 2000 (CSLLEA; ICPSR #3484).

Concerning the structure of network ties, models for the general characteristics of the named contact show that features of the responding agency significantly influenced the choice of network contact. Similarly, the analysis of which particular agency was chosen show that agency characteristics and geographical distance were important factors in this choice. Agencies tended to choose larger agencies as contacts and there was a tendency to choose agencies of the same type, although in some analyses this tendency appeared more pronounced for city than for county agencies. We crudely identified "relative experts" in various domains of police planning, so even after accounting for structural influences on contact choice, agencies seemed to perceive different agencies as more or less valuable sources of information. Expert agencies appeared more salient in domains that are likely more interesting to the general public.

For the impact of network ties on innovation, we examined several ways of operationalizing network ties. Estimated network effects were almost always in the expected

direction; in analyses of adoption, effects often did not reach statistical significance, but they often did in analyses of change. When the network specification was based on change in the contact's characteristics, the least intuitive way to conceptualize network influences, no effects were significant and many were not of the expected sign. When specified more intuitively as difference between the responding agency's and the contact's characteristics, effects were more often significant and of the expected sign. While it is possible that network influences on innovation are difficult to detect in a relatively small sample, and there are other features of the data that may contribute to inconsistent findings, a large enough proportion of significant network effects were found to suggest that there likely are real effects of network ties on innovation.

Executive Summary

Literature Review

- Relevant literature includes that on network influences on innovation in general, organizational networks, and research on police networks specifically.
- The literature is quite convincing on the presence of network influences on innovation, although there are still areas of controversy.
- On properties of organizational networks, an important issue is whether the main motivation for network ties is homophily (contact with similar agencies) or exchange (contact with dissimilar agencies who may offer otherwise unobtainable information or, more generally, resources).
- Existing studies of police networks have addressed the relationship between communication and "innovativeness", agencies' stated reasons for a particular choice of agency to contact, and whether willingness to contact others is related to innovation adoption.

Analysis of Network Data

Main results in the analysis of the police network data include:

- Choice of an in-state contact was less likely for larger than for smaller agencies, and for state or city agencies relative to county agencies. Rather than size or type per se, it appears that relative size (within the state) was the most important factor.
- Choice of a contact of the same type (city, county, or state) was more likely for larger agencies and for city and state agencies relative to county agencies. Same-state contacts

were more likely to be same-type.

- There was an overall tendency to choose larger agencies as contacts; while, as logically expected, choice of a larger contact was more likely for smaller agencies, effects of responding agency characteristics were not consistently significant.
- There appears to be some size-based asymmetry in comparing most frequently contacted and most frequently contacting agencies. However the nature of the data prevents a completely satisfactory analysis of asymmetry.
- Looking at the reported ties in specific domains of policing, choices in the various domains appear to be somewhat distinct from the general most frequently contacted agency. Within domains there were clear tendencies for agencies to choose contacts of the same type, with city and county agencies acting more similar to each other than either did to state agencies.
- “Relative experts” could be identified in many domains. Identification of experts seemed clearer in more publicly salient domains.
- We examined models for the particular choice of an agency named as the most frequent general contact among the possible contacts in the responding agency’s state. Influences of similarity of the respondent’s and a potential contact’s type, of the ratio between the respondent’s and a potential contact’s size, and the geographical distance between the respondent and a potential contact were all apparent. While results were, to some extent, what would be expected intuitively, interpretation was complicated because of interactions among these factors.
- For out-of-state choices, effects of similarity of the respondent’s and a potential contact’s

type, of the ratio between the respondent's and a potential contact's size, and the geographical distance between the respondent and a potential contact were all observed, although without interactions among these factors.

Network Ties and Innovation

- No significant network effects were apparent for adoption of community policing, or change (from 1997 to 2000) in the presence or absence of community policing.
- For adoption of geographic assignment of detectives, larger agencies were more likely to adopt, but network effects did not quite reach statistical significance. For change in the presence of geographic assignment of detectives, significant network effects were found, indicating that responding agencies were more likely to change if their named network contact differed from them in 1997 or in 2000.
- City agencies (compared to county) and larger agencies were more likely to initiate encouragement of SARA problem-solving, but no network effect was observed. However network effects (in the expected direction) were seen for change in the encouragement of SARA problem-solving.
- For adoption of computer use for resource allocation, larger departments were more likely to adopt, but significant network effects were not observed. For change in computer use for resource allocation, none of the modeled factors had significant effects.
- City agencies (compared to county) and larger agencies were more likely to adopt computer use for crime mapping. Significant network effects were also apparent: agencies whose network contact had computer use for crime mapping were more likely to

adopt. For change in computer use for crime mapping, agency type and size did not have significant impacts, but again network effects were significant.

Policy Implications

- Different processes may be at work for different innovations, and programs to encourage innovation must recognize this.
- As results suggest that departments do seek out experts, the research community needs to devote resources to systematically identifying and publicizing empirically assessed expertise.
- Efforts can be made to induce useful ties between particular agencies, although it needs to be decided whether such inducement should follow or cut against the "natural" process of tie formation.
- Further research is needed on networks and innovation, including collection of data more closely matched with these research questions.

0. Introduction

This report summarizes results from the project "Police Innovations and the Structure of Informal Communication Between Police Agencies: Network and LEMAS Data" (NIJ #2003-IJ-CX-1002). The project's goal was to investigate both the pattern of network ties among American police agencies and the consequences of these ties for adoption of police innovations. The network data were drawn from the Weiss (1997a) data set Communication of Innovation in Policing in the United States (ICPSR #2480). These data represent informal communication reported by planners at sampled police agencies with their counterparts at other agencies on various issues of police department interest. Data on agency characteristics and practices were drawn from the Law Enforcement Management and Administrative Statistics (LEMAS) data sets for 1997, 1999 and 2000 (ICPSR #2700, #3079 and #3565). Some data had to be obtained from the Census of State and Local Law Enforcement Agencies 2000 (CSLLEA; ICPSR #3484). Innovation was measured by the change in reported agency characteristics or practices between the 1997 and 2000 administrations of LEMAS.

This report is organized into the following sections. First, we give a brief overview of existing literature that is especially relevant to this project. The project's concerns actually span a substantial breadth of literature in criminal justice, sociology and organizational studies. It would beyond the project's scope to give a comprehensive review of all that these literatures could contribute, so we will focus on some important highlights. In the second part of the report, we will discuss decisions that were made in processing the network data for this project, and describe our plan for the research. We will also note some limitations that prevented some potentially interesting analyses. The third section of the report focuses on direct analysis of the network data. Here we try to understand which agencies are tied to which others, and how agency characteristics influence choice of informal communication contacts (or “alters”, in the language of social networks). The report’s fourth part tackles the question of the relationship between the reported network ties and adoption of innovations. We look at practices with respect to community policing and aspects of the agencies’ use of computer technology. It is important to note that we are studying network influences on innovation adoption, not the process of innovation in general. The final section gives summary conclusions and some tentative policy implications.

1. Brief Literature Review

A study of informal communication between police agencies and its impact on adoption of innovation can draw on several vast literatures. Here we focus on some key recent pieces of the organizational networks and policing literatures that are most relevant to our study. A full review of these literatures is, of course, beyond the scope of the present work. As such, we do not include a general overview of social networks and methods for social network analysis; Wasserman and Faust (1994) is an excellent source for such a review.

1.1 Organizational Networks

There has long been recognition of the importance of social networks for adoption of innovations, and over the years a substantial body of empirical work has developed. Rogers (1962) and Coleman, Katz, and Mendel (1963) were early classics, and research in this tradition has continued to the present. While some of this research looks at networks of individual people, in much of this work the network actors are organizations. Among others, Rothwell (1991), Kearns (1992), and Powell, Koput and Smith-Doerr (1996) examined the impact of organizational networks on adoption of innovations. Viewed somewhat more broadly, adoption of innovation may be seen as one of many possible consequences of the structure of organizational networks (Oliver and Ebers, 1998). That is, many organizational practices may be influenced by network position, including many that are not precisely adoption of innovations. Effects of network position on organizational behavior were shown in studies such as Galaskiewicz and Wasserman (1989), Galaskiewicz and Burt (1991), Mizruchi (1993), Sandell (2002), and Williamson and Cable (2003). Through these and many other works, the importance of networks for organizational behavior has been well-established.

However that is not to say there are no controversial questions in this area. One question is whether different types of ties have different implications for innovation, as suggested by Kelley and Brooks (1991). Another important issue is the distinction between effects of network ties and the effects of spatial proximity (see for instance the discussion in Strang and Soule [1998]). Because network ties are more likely to be established with nearby actors, it is difficult to determine whether network position or physical location is influencing the adoption of innovations or practices. Heanue and Johnson (2001), for instance, showed effects of spatial proximity (as well as effects of other kinds of organizational similarity that are not necessarily spatially based). Sandell (2002), on the other hand, found little impact of spatial proximity, although he noted that the spatial concentration of the firms in his study would make it difficult to find strong effects of proximity. Wejnert (2002) argued that many apparent spatial effects become less important when controlling for network ties and other kinds of organizational similarity. We should note that in our study available data did not permit a satisfactory distinction between spatial and network effects.

Another important question is whether innovation is most influenced by “cohesion” or “structural equivalence”. Cohesion refers to direct and indirect ties between actors; in this image, ties to innovators would, presumably, make an actor more likely to adopt. Structural equivalence refers to the similarity of two (or more) actors’ patterns of ties to others, whether or not those actors are tied to each other. In this image, structurally equivalent actors occupy similar roles in the network, and an actor would be more likely to adopt an innovation if those actors structurally equivalent to it had done so. Studies such as Galaskiewicz and Wasserman

(1989), Galaskiewicz and Burt (1991), and Mizruchi (1993) have attempted to determine which conception of network position best captures network effects on innovation. (See also Strang and Soule [1998].) Our data in fact only permitted a cohesion-based approach that does not rely on indirect ties.

But before considering network influences on diffusion of innovation, it is important to ask what leads to network ties between particular organizational actors. For example, networks of individuals typically display considerable "homophily", in which individuals' ties tend to be with others who are similar to them in important respects. The same may be true of organizational networks. In Lincoln and McBride's (1985) study of human service providers, for example, network ties were homophilous for some organizational characteristics. Wholey and Huonker (1993) studied non-profit agencies serving youth in Indianapolis, and examined whether network ties seemed more consistent with the homophily account or with an "exchange" argument, in which agencies seek ties with dissimilar agencies (that are likely to offer resources or expertise unavailable in contacts with similar alters). Although an interdependence argument may be well-suited to studies of business firms' alliances (see Gulati and Gargiulo [1998]), the homophily perspective seemed better supported in Wholey and Huonker's data. In their study of community organizations, Banaszak-Holl, Allen, Mor, and Schott (1998) noted that while ties were expected to be homophilous, structurally equivalent organizations (occupying similar positions in the network, so that their roles in the system are similar) did not need to be of a similar type. Still, ties between those not occupying the same position (with different roles) did tend to be between similar organizations.

Studies of organizational networks offer some complications that are absent in networks of individuals. For instance, can ties between organizations be separated from ties between individual members of the organizations? Johnson (1992) suggested that communication between organizations is in fact best viewed as communication between individuals in those organizations. Woodard and Doreian (1994) found that for the pattern and types of transactions between mental health services agencies, it mattered whether contact was initiated by the agency director or by agency staff members. Kearns' (1989) study of contacts between municipal managers on computer issues found that while geographic proximity influenced the choice of contacts, managers who were most asked for advice did tend to have more actual knowledge of computers. In our study, the nature of the data required that we take ties between individual police planners as ties between the planners' agencies. We believe this is reasonable, especially as we attempt to examine large-scale patterns in these ties. Clearly, though, it is possible that other kinds of contacts between agencies could have resulted in different patterns.

1.2 Studies of police networks

There have been many studies of various sorts of innovations in policing and management of police agencies. Important examples include Monkkonen (1981), Skolnick and Bayley (1986), Weisburd, Uchida, and Green (1993), Moore, Sparrow and Spelman (1997), and King (2000); see also chapter 3 in National Research Council (2004). Given the general literature linking innovation to network ties, it is natural to study informal communication between police agencies as a way to better understand police innovations. But, in fact, before Weiss' (1997b, 1998a, 1998b) studies there was little research on informal communication between police agencies. Weiss' (1997b) first study investigated the impact of communication, imitation of other agencies, and officials' participation in national police organizations on "innovativeness". Weiss found that more "connected" departments were more innovative, supporting the notion that ties between departments are important for the innovation process. However the data for that study did not actually report measurements of network ties from particular departments to particular other departments. For instance, departments were asked *whether* they contact other departments for research purposes, but apparently not *which* departments (if any) were contacted, or the nature of these contacts. So while suggestive of the role of network ties in police agency innovation, the data used in that research did not allow for an explicit examination of these ties and their impact on innovation.

To remedy this, Weiss (1997a) collected the much richer Communication of Innovation in Policing in the United States data set (Weiss, 1997a). These data provided much more detailed information on informal communication. Planners in the responding departments were asked to name particular other departments with which they communicated in general and on specific policing issues. Weiss (1998a, 1998b) discussed some aspects of this network, such as how planners within the agencies chose which other agencies to contact, the mode of contact (telephone, mail, electronic mail, and so on), and the volume of information requests received. The analyses reported in Weiss (1998a, 1998b) were primarily descriptive analyses of aspects of communication like mode and frequency of contact, and did not examine the details of the network structure (which agencies choose which contacts) and the impact of the structure on innovation.

Chamard's (2003) dissertation appeared after our original proposal was submitted, and part of her research comes closest of existing (and known) studies to the intent and goals of our project. Chamard conducted quite extensive research on the adoption of crime mapping; the aspect of her research that is most relevant to our study was her work on potential network influences on adoption of crime mapping among police departments in New Jersey. To collect network information, Chamard asked New Jersey departments about which other departments they were in contact with concerning crime mapping. After asking whether departments sought (or were sources of) information on crime mapping, those which did (or were) were asked "Which of those departments have you asked about crime mapping most often?" (p. 189), and "Which police department asks your department about crime mapping most often?" (p. 190). Subsequent questions asked about the frequency and nature of this contact. Chamard's dissertation reports on many features of these data, and we will briefly review the results that are most important for our work.

Only a small minority of agencies reported contacting or being contacted by other departments, and a minority of those who contacted others about mapping actually adopted the innovation. But adoption was significantly more likely among those who contacted other agencies than those that did not (Chamard 2003, p. 110); Chamard notes that it is not clear whether contact preceded or followed adoption of mapping. The most frequent "most important reason" for the particular choice of agency to contact was "The other department faces the same issues we do" (42%), followed by "We have good contacts at the other department" (21%). Geographic proximity (12%) and similarity in size (7%) were cited as "most important" relatively infrequently. (Chamard 2003, p. 114). However it may be that "faces the same issues" has important components of size and geographic location. Also, proximity and size similarity were relatively often cited as reasons, not necessarily most important, for the choice of contact (50% and 25% respectively) (Chamard 2003, p. 114).

Chamard (2003) also analyzed "advisor-advisee" agency dyads. There were relatively few usable dyads for the analysis, but it appeared that there was a tendency for advisors to adopt mapping before advisees. The two departments in a dyad tended to be geographically near (median 12 miles); in dyads with both from New Jersey, in over 60% the departments were located in the same county. It did not appear that long distance dyads were the result of departments seeking advice from large but relatively distant departments, but distances did tend to be greater when the advisor had adopted mapping than when it had not, and size was correlated with adoption. Chamard (2003, p. 129) suggested that information appeared to be "flowing from large, innovative departments in Essex and Hudson counties, to the somewhat smaller, yet still innovative departments in Monmouth and Ocean counties, which in turn distribute information to their even smaller, less innovative, more local peers." Note again, however, that even among those departments contacting other agencies on crime mapping, most did not adopt mapping. So the information flow did not assure adoption of the innovation.

2. Data and Plan for Analysis

2.1 Data

LEMAS and CSLLEA data are quite well-known in the research community, so we will not discuss them at length. We focused on LEMAS data from 1997 and 2000, because we were interested in change in agency characteristics (in particular, the influence of network ties on such change). The first date was chosen to be relatively close to the collection of the network data. (Network surveys were mailed to sampled agencies in March, 1996, and returned by June, 1996 [Weiss 1997a].) While we had originally considered comparing 1997 and 1999, we decided that a somewhat later ending date would perhaps give more opportunity to detect network influences on agency characteristics. (We did take advantage of some 1999 data in certain analyses.) We used CSLLEA for basic data on agencies excluded from LEMAS, and for constructing complete lists of agencies in the various states.

Weiss' (1997a) Communication of Innovation in Policing in the United States data set recorded data on general informal communication between police agencies, as well as data on informal communication regarding a number of specific planning issues. The sample consisted of 360 local police departments (including county police departments), 43 state police agencies, and 13 sheriff's departments that responded to a survey of local city and county police agencies, and all state police agencies.[1] Data on inter-agency cooperation in criminal investigations were not collected. Rather surveys were directed to planners (specifically "the commander of the department's planning and research unit") in the responding agencies. For our research, key items from Weiss' survey were Question 1 ("What law enforcement agency, if any, do you contact <u>most frequently</u> when you are seeking information to use in planning and research?"), Question 6 ("Which law enforcement agency, if any, contacts **your department** most frequently for information on research and planning?"), and Question 10 ("The law enforcement agency you contact might vary according to the topic of your research. For each of the following topics, please list the law enforcement agency that you would **most likely contact** for information about its programs and policies," with the following topics listed: domestic violence, deadly force, gangs, community policing, problem-oriented policing, drug enforcement strategy, civil liability, labor relations, personnel administration, accreditation, police traffic services.)

The Weiss (1997a) data set includes substantial information on informal communication between police agencies. However there are a number of challenges inherent in using the network data. First, many of the network items were left blank by responding agencies, so that the effective sample sizes for most possible analyses are considerably smaller than suggested by the figures given above. While it is possible that an agency had no contacts of the type being asked about in a question, especially for the general questions, this was probably relatively rare. Likely most blank items indicated non-response rather than the genuine absence of any ties. Also, the transcribed responses to the questions of interest included many obvious misspellings, which could either have been introduced in transcription or present in the original form returned by the agency. Third, even in cases of apparently correct spelling, there were many ambiguities in the responses. These ambiguities included responses with no specific geographic information, such as "sheriff", responses with a city name but no state (when more than one state has a city of the given name), and responses listing a name shared by a city and county agency but no indication of which. None of the particular ambiguities occurred too frequently, but together they represented more than a trivial minority of responses. Finally, there were some instances of an agency naming itself; we considered these blank.

There is nothing that can reasonably be done for the challenge of blank responses. But for the second and third challenges, we adopted strategies that attempted to be conservative but still allow for as much salvaged data as reasonably possible. Of course these strategies did not lead to a usable response in all cases, nor did they permit 100% confidence that we captured the intent of the responding agency when salvaging a response, but we believe that the number of errors introduced by our procedures was small. For the second challenge, misspellings, we tried to first identify agencies in the same state whose names could likely have been misspelled as shown in the data. If none were found, we considered large out-of-state agencies that could have led to the misspelling. We were able to find a reasonable match in the large majority of misspellings.

The third challenge—ambiguities—was more difficult. Responses of “sheriff” were assumed to be the sheriff in the agency’s home county, and “state police” was assumed to mean the state police in the agency’s home state. For city names that were not accompanied by state identification, we first checked if there was a city of that name in the agency’s home state. If there was such a city, we typically assumed that it was the intended response. In some cases, however, this city’s population was so much smaller than that served by the responding agency that we thought it was unlikely to be the intended response. In such cases we considered larger cities of that name in other states, and chose either a nationally prominent large city or a regionally prominent city in a nearby state. When a city police department shared the name of a county police or sheriff’s department, we assumed that the city department was the intended response. We were not entirely at ease with this choice, but relatively few cases involved this ambiguity. Also, some counties have both a county police and sheriff's department; we did not attempt to distinguish these, and took either to represent the county. Again, it is impossible to have complete confidence in the correctness of the decisions made in resolving ambiguities, but we do not think that many of the resolved responses were incorrect—certainly too few to distort overall patterns in any significant way.

2.2 Plan for Analysis of Network Data

The most compelling sort of network analysis involves study of relations among all members of some bounded set of actors. Such data lead to the familiar "sociograms" of points and lines between them, showing each actor and all its ties to other actors, and permits the most satisfactory analysis of structural features of the network. This sort of ideal analysis is not possible here. First, the natural bounded set of actors would consist of all American police agencies, not just the relatively small number sampled in Weiss (1997a). Second, the key survey questions asked for the "most frequently" contacted or contacting agency, not all agencies with whom the responding agency had contact. In fact many responding agencies ignored the instructions and listed multiple contacts, and we used those data in some of our analyses. It is clearly it is wrong to assume that an agency's only contacts were those reported in response to the survey questions. For instance, it is highly likely that many agencies that listed only one contact would have listed more had the survey instructions allowed that. (In fact one respondent objected that "the assumption of single pint [sic] contact is too limiting".)

Because the Weiss survey was originally directed to planners at all local agencies with at least 100 sworn officers, one might imagine an analysis of the bounded network of such agencies, with attention restricted to the first listed contact (to address the problem of additional unnamed contacts). The restriction would mean a very sparse network, but otherwise still permit some kinds of structural analysis. An immediate obstacle is survey non-response: 28% of these agencies did not respond to the survey. Would it be possible to further bound the group, to the remaining responding agencies? While not a very natural group, perhaps this would allow traditional structural analysis. Unfortunately such an analysis would also be inappropriate.

We can see why by focusing on the 362 city and county agencies whose data were included in our study, and on Question 1 (the most frequent contact). For this bounding of the set of actors, only named contacts that were also city and county agencies are relevant. 220 of the agencies listed a city or county agency first for Question 1, but only 157 of these were among the 362 agencies in our study. Immediately, then, an analysis of the 362-agency-network would indicate no contact for 63 agencies which actually reported one, though this could be tolerated as a consequence of the bounding. Breaking down the responses of the other 142 agencies to Question 1, one category of responses included 5 agencies that listed a city or county department later than first in their list; changing the criterion a bit would allow these contacts to be represented in the network. Other categories indicate the problem.

The largest number of agencies (50) were categorized as the respondent having listed only some agency, group or office (or a set of such) that was not a city or county police or sheriff's department for Question 1. Responses in this category included the FBI, IACP, state police, the local District Attorney, and so on. It seems unlikely that none of these 50 agencies had information-seeking contact with any of the 362 included agencies, particularly given the survey instructions to list only one contact. The next largest category, with 41 agencies, was that in which a specific city or county department was not named, but the language clearly suggested contact with such an agency (or agencies). Example responses here included "neighboring police depts.", "Texas cities", and "various agencies close to our own size". Given such responses, it is unrealistic to assume that none of these respondents had any contacts among the 362 agencies. The next category of 29 agencies included those with even vaguer responses, in which it was unclear if city or county, rather than state or national, agencies were intended. This category included such responses as "no specific agency—several", and "varies greatly depending on the topic area". Again it is likely that a good number of these vague responses actually referred to contacts with agencies among the 362.

Clearly assuming no contact for all the agencies in these categories would introduce a great deal of distortion into any structural analysis, but the data do not allow identification of any specific contacts that existed. To be sure, some actually had no contact with any of the 362 agencies. In fact 6 agencies explicitly said that they made no information-seeking contact (for example, "none—all planning and research is handled internally"). 11 agencies left Question 1 blank; while there is no way to confirm that these in fact had no contact, it is possible. But even so, the other categories of responses offer quite substantial evidence that an instance of a respondent naming no city or county agencies as contacts did not reliably indicate that the respondent truly had no such contacts. In light of this, any structural analysis of the entire 362 agency network would not be trustworthy.[2] We had originally thought that perhaps there could be analysis of the complete network of state police agencies, but, as with the city or county agencies, there was enough non-response to network questions by the sampled state police agencies that such an analysis would be unreasonable.

The nature of the data was therefore similar to that of the 1985 General Social Survey's network data. There sampled Americans were asked to report on a limited number of their network ties. Naturally this does not lead to a diagram showing the network of all Americans, but it still allows for a variety of important analyses of Americans' personal networks. The Weiss data likewise permit valuable analyses of the structure of informal inter-agency communication, even though one cannot construct a diagram of the complete American police agency network.

With this restriction in mind, the first part of our study, analyses of the network items, focused on the nature of the contact choices made by agencies. There were enough different analyses that it would be confusing to discuss them in detail at this point, but all attempted to use agency characteristics to explain aspects of the agency's network ties. In some cases our interest was in the nature of the agency (or agencies) named as a contact (or contacts); for instance, was the named alter from the same state as the responding agency? In other analyses, we were interested in which particular agency was named; this requires comparison of the characteristics of the responding agency with those of named and unnamed agencies, and was guided by the homophily and exchange perspectives reviewed above.

As characteristics of the responding agency, we used size and type (city, county, or state agency; as noted above, we discarded the single tribal agency in the data), including, for some analyses, whether the agency was the state's largest municipal or county agency. Originally we had considered a variety of other agency characteristics reported in LEMAS, but decided not to use them. One reason was the relatively limited sample sizes, which raised concerns for analyses with a large number of independent variables. Another was that some analyses required information on both the responding and the named (or potentially named) agencies, and many agencies were not included in LEMAS. A possible objection to using size is that only a minority of the responding agencies cited “the other agency is the same size as ours” as a reason why a particular agency was contacted most frequently (Weiss 1997a). But this does not mean that size was not salient in the choices of network contacts; a trend toward contacting larger agencies, for instance, would have resulted in few positive responses to this question. So for analyses requiring agency characteristics or an assessment of similarity between responding and potential contact agencies, we focused on size and type.

Of course using size required making another decision, as there are a variety of possible size measures. Population is the most universally available measure, and we chose to use the population (in fact we used the log of population in our models) as of the 2000 census of the agency’s city or county (most of our analyses did not include state agencies because of the difficulty in comparing sizes of state agencies with city/county agencies) as the size measure. We did not use a count of the authorized or actual number of officers in the department, even though CSLLEA should provide those for agencies not in LEMAS. But although CSLLEA is intended to give complete coverage of American agencies, a few agencies of interest in our study were omitted. So to allow as complete data as possible, we used population as our size measure. (For convenience, we simply say “population” rather than “population served”.) In practice, the possible size measures were highly correlated, at least within an agency type. This choice, then, should not have much practical effect on results.

Some of the literature discussed above suggested that the jurisdiction’s crime rate may be an important agency characteristic for the sort of analyses that interested us. That is, agencies may see others whose communities face similar levels of crime as good choices to contact. (Many agencies cited “the other agency seems to face the same issues/problems we do” as a reason for their primary contact [Weiss 1997a].) In the end we decided not to use crime rate in our analyses. For one, use of crime rate seemed to us to exacerbate the difficulty of considering both city and county agencies in an analysis. But more importantly, the similarity suggested by similarity of the crime rates in two agencies’ jurisdictions can often be artificial. A very small and very large agency simply will not think they are facing the same sort of issues or problems just because their jurisdictions happen to have similar calculated crime rates. This is particularly true because crime rates for agencies in small jurisdictions are especially vulnerable to chance fluctuations from a small number of crimes. While it is possible to construct new measures combining similarity of size and crime rate, we did not consider any of those entirely satisfactory.

2.3 Plan for Analysis of Innovation Data

For the second part of our study, we examined the relationship between innovation and network contacts. (Precisely, we were interested in innovation adoption and change in practices, not innovation in the sense of which agency was the first in the nation to engage in some practice. For convenience, in the text to follow we often write innovation as shorthand for innovation adoption and change in practices.) The primary goal was to discern if the presence of a program or characteristic in an agency’s primary network contact made it more or less likely for the agency to adopt that program or characteristic. As with the first part of the study, many details of the analyses will be discussed below in the presentation of the results. Because information on programs or characteristics was drawn from the various years of LEMAS, analyses were necessarily limited to cases in which the responding agency and its named alter were both included in the appropriate administrations of LEMAS. We refer to changes in the presence or absence of these programs or characteristics as “innovation”, but of course the data here do not speak to the impact (positive, negative or absent) of these changes on police effectiveness. (For example, Manning’s [1992a; 1992b;] works suggest that advances in the information technology available to police have relatively little impact. Consideration of such questions was beyond the scope of our study.)

For specific programs and characteristics to be examined in our study, we looked to community policing and use of computer technology. These were intended to roughly represent two quite different types of policing innovation. The police innovation literature suggests such a difference, although as Moore et al. (1997) noted, rigid classification of particular innovations can be difficult. The first type, represented in our study by community policing, consists of innovations that would be highly visible and interesting to the public and, possibly, politically contentious. In National Research Council’s (2004) typology, such innovations would likely be “stimulated by local governance”, although the “social learning” process would be at work also. The second type, represented here by use of computer technology, consists of innovations that are primarily of technical interest to law enforcement professionals. Of course there can be public interest in any aspect of policing, and innovations of the second sort could attract attention if they involved substantial financial burdens, or were thought to result in great increases in police effectiveness. But by and large innovations of the second sort will not be of broad public interest or politically contentious.

Examining the impact of network ties on these two very different types of innovation helps us understand both whether network effects exist at all and, if they do, whether effects are felt differently for different sorts of innovation. Of course the available data reported on only one type of network tie; Weiss (2001; as cited in National Research Council [2004]) suggested that different sorts of ties would be important for different innovations. With data on only one particular kind of tie between agencies, absent or relatively small apparent network effects could indicate that some other type of tie would be relevant for the innovation being studied.

Larger departments may have been more or less likely to adopt these innovations than smaller departments. Or, larger agencies may have been more likely to adopt earlier, and thus did not appear as adopters in the data here. Our analyses controlled for size and type (city or county) of agency, but the issue of prior adoption could have attenuated estimated network effects. It was natural to conceive of the computer technology measures as dichotomous, indicating presence or absence of a characteristic, as the LEMAS data did not generally give information on the degree of technology use in an agency. For community policing, on the other hand, some numerical measures would have been possible, such as the number of officers in community policing units. We did not use these, focusing exclusively on dichotomous (presence/absence) measures. The numerical measures seemed potentially more sensitive to changes due to redefined community policing activities or missions, and we decided that it would be more cautious to rely on the dichotomous measures only.

Ideally we would have wanted our analyses to distinguish between network and spatial effects, as this is an important idea in the literature. However with relatively few observations, and the clear possibility of spatial influences on network ties, it was not realistic to examine both a network effect (based on characteristics of the named network contact) and a spatial effect (based, say, on characteristics of the nearest large, or larger, agency). It is possible, then, that estimated network effects either included spatial effects or were dampened by not controlling for spatial effects. Likewise, the nature of the network data did not allow us to identify structurally equivalent actors (as that would require more complete data on the police agency network, not just the sample of respondents). We were therefore unable to examine the possibility of different results from defining network variables based on structural equivalence rather than those based on cohesion.

It is important to note one implication of our interest interested in network influences on innovation adoption (or change in practices). The nature of the investigation meant that certain types of likely real influences on innovation were not considered. To be sure, adequate assessment of network effects requires that other important factors be controlled, and our examination of network effects took place in the context of multivariate models. But this framework does not allow a consideration of, say, the impact of an article in *The Police Chief* on some innovation on the likelihood of its adoption. With all agencies (in principle, at least) exposed to such material, it cannot be considered in a model for which agencies did or did not change their practices. (This would require some measure of the exposure of each agency to the potential influence, and such data are not apt to be available.) In a different sort of study, it might be feasible to examine such influences on the different frequencies with which different innovations had been adopted across all agencies. But we did investigate the sort of influences that would potentially affect all agencies.

3. Analysis of the Network Data

In this section we report the results of our analysis of the network data, with models using characteristics of the responding agencies to predict the type of agency named as a network contact. Some models focus on the particular agency named. Regression-type tables in this section report results of logistic regression (logit) models for a dichotomous dependent variable. With $p_i = \Pr\{Y_i = 1\}$, and independent variables $X_1, \ldots, X_K$, the logit model can be written as

$\log(p_i / 1 - p_i) = \beta_0 + \sum_{j=1}^{K} \beta_j X_{ij}$. Note that an estimate b_j is interpreted as the estimated effect of X_j, holding other independent variables constant, on the log odds that $Y_i = 1$; $\exp(b_j)$ is the estimated multiplicative effect on the odds that $Y_i = 1$. Neither figure is interpreted as the effect on $\Pr\{Y_i = 1\}$. Standard errors are shown in parentheses throughout. Significance tests (tests of the hypothesis that $\beta_j = 0$) typically rely on the z-ratio, the estimated coefficient divided by its standard error, or the Wald statistic, this ratio squared. We report p-values based on the z-ratio in the tables below, with a pound sign indicating $p < .10$, one asterisk indicating $p < .05$, and two asterisks indicating $p < .01$. Nested models may be compared using log-likelihood for each model; when the simpler model is "true", differences in -2 x log-likelihood are distributed as chi-square, with degrees of freedom given by the difference in parameters between the two nested models. As mentioned above, different analyses used different sample sizes because of non-response to various questions. Each table reports the sample size for the analysis being presented.

3.1 Most Frequently Contacted Agency

Our first analyses focus on survey Question 1 (giving the agency most frequently contacted in general). The subsections below report on many aspects of the responding agency's choice of most frequently contacted alter.

3.1.0 Presence or Absence of a Response

As a preliminary analysis, we considered whether size (measured as log population) and type of agency could predict the presence of a usable response to this question. "County" was the omitted category for the agency type variable.

Table 3.1.0.1 Dependent Variable: Presence (1) or Absence (0) of a Usable Response to Question 1

	Model 1	Model 2
Intercept	3.629	3.942
Log Population	-0.231 (0.074)**	-0.212 (0.120)#
City Agency		-0.547 (0.495)
State Agency		-0.772 (0.573)
-2xLL	494.799	490.434
N	405	405

Comparison of the models suggests that agency type was not related to response, while there did seem to be some population effect. It is perhaps counter-intuitive that the estimated population effect was negative, indicating that larger agencies were less likely to give a usable response to Q1. This could reflect a genuine tendency for larger agencies to seek less input from others, or perhaps the task of completing the survey seemed less pressing to personnel at larger agencies.

Note, though, that this preliminary analysis included state agencies, so the population variable was somewhat problematic in this analysis. For the next table, we repeated the analysis with state agencies excluded.

Table 3.1.0.2 Dependent Variable: Presence (1) or Absence (0) of a Usable Response to Question 1; State Agencies Excluded

	Model 1	Model 2
Intercept	3.206	4.697
Log Population	-0.193 (0.117)#	-0.269 (0.131)*
City Agency		-0.639 (0.505)
-2xLL	431.503	429.797
N	362	362

In the comparison of the models, Model 1 was preferred, and the population effect was only borderline significant there. The negative sign remained, but with state agencies excluded it is less clear whether there was a real population effect at all.

3.1.1 <u>In-state Contact Choice</u>

Our first main analysis considered the location—in-state or out-of-state—of the responding agency's reported most frequent contact. This analysis necessarily used only those agencies that named a contact, so the sample size was reduced substantially. As discussed above, many agencies named more than one contact, even though the survey instructions were to name the single most frequent contact. In general, when more than one agency was named, we used the first named. That seemed reasonable in general, but there were situations in which it appeared that the responding agencies simply listed alters in alphabetical order, not order of importance as a contact. Such situations were relatively few, however, and we do not believe this rule would have a major impact on results. And, some of our analyses took advantage of all the named contacts. For these analyses, we also treated a national agency such as the FBI or DEA as out-of-state, even though such agencies have local field offices.

The following table reports on models estimating effects of size and agency type on the state location of the most frequently contacted agency (again with "county" as the omitted category of agency type). The raw proportion of in-state choices was quite high (76%; 213 of 279), suggesting a general tendency toward in-state contacts, but characteristics of particular agencies still may have influenced the choice of in- or out-of-state contacts.

Table 3.1.1.1 Dependent Variable: In-state (1) or Out-of-state (0) Response to Question 1

	Model 1	Model 2
Intercept	2.251	10.490
Log Population		-0.621 (0.185)**
City Agency	-0.773 (0.762)	-1.677 (0.822)*
State Agency	-5.247 (1.266)**	-4.228 (1.298)**
-2xLL	248.703	237.385
N	279	279

Focusing on the preferred Model 2, the estimated effects seem sensible. The population effect indicated that larger agencies were less likely to make an in-state choice. The estimate says that a 10% increase in population resulted in a 6% reduction in the odds of an in-state choice. This effect is consistent with a tendency for respondents to contact larger agencies; the larger the agency, the less likely there was to be an available in-state choice of larger size. The coefficient for state agency was very large (in absolute value). The estimated odds of an in-state choice by a state agency were only about 1.5% as large as the odds of an in-state choice by a county agency. Clearly state agencies did not in general see city and county agencies as helpful resources for planning. Likewise city agencies were substantially less likely to seek in-state help than county agencies.

For the next analysis, we slightly changed the definition of the dependent variable, so that it indicated whether the responding agency named *any* in-state contacts for Question 1 (taking some advantage of multiple names given for Question 1).

Table 3.1.1.2 Dependent Variable: Any In-state (1) or No In-state (0) Response to Question 1

	Model 1	Model 2
Intercept	2.251	8.330
Log Population		-0.459 (0.190)*
City Agency	-0.532 (0.765)	-1.185 (0.819)
State Agency	-4.503 (1.051)**	-3.684 (1.096)**
-2xLL	228.336	222.684
N	279	279

Comparing results for Model 2 to those in Table 3.1.1.1, the estimated population effect was somewhat reduced, and state-county and city-county differences were smaller (with the city-county difference no longer statistically significant). But results were not dramatically different.

As before, it was interesting to repeat this analysis with state agencies excluded. Not only did this permit a more consistent treatment of population, it allowed us to explore further the idea that a tendency to choose larger agencies leads, in some instances, to out-of-state choices. Even if this tendency were present, it would not mean that the largest department in the state has to go out-of-state for its most frequent contact. First, this tendency would not be absolute, and, second, even if it were, the local state police would be an alternative.

Before examining logit models, some descriptive statistics give a sense of this tendency. Of the 220 city and county agencies whose most frequent (or first named) contact was another city or county agency, 161 (73%) named a larger population agency. If restricted to responding city agencies only, this proportion was 75% (152 out of 203). Of course that left a large number of exceptions; in fact the ratio of responding agency's population to named agency's population was as small as 0.074 in these data, so there were instances of agencies naming much smaller agencies as their most frequent contact. But still these descriptive statistics suggest that the main impulse was to contact larger agencies for planning assistance.

For the logit models, we included an independent variable indicating whether the responding agency was the largest population department of its type (city or county) in its state.

Table 3.1.1.3 Dependent Variable: In-state (1) or Out-of-state (0) Response to Question 1; State Agencies Excluded

	Model 1	Model 2	Model 3
Intercept	10.603	1.787	6.619
Log Population	-0.629 (0.188)**		-0.305 (0.225)
City Agency	-1.690 (0.824)*		-1.332 (0.864)
Largest of Type in State		-2.075 (0.478)**	-1.705 (0.562)**
-2xLL	229.395	223.589	220.210
N	258	258	258

Model 1 parallels Model 2 in Table 3.1.1.1, and it appears that excluding state agencies did not change results substantively. Adding the indicator of largest of type in state (Model 3) improved fit significantly. It seems that the apparent population effect was in large part the result of a tendency to seek larger agencies for help, rather than an absolute impact of population. (In Model 3, the coefficient for population was still negative, but no longer statistically significant; the city-county difference was also no longer statistically significant.) In fact Model 3 was not a statistically significant improvement over the very simple Model 2. In Model 2, the estimated coefficient for largest of type in state indicated that the odds of an in-state choice for an agency that was its state's largest (of its type) were only 13% of these odds for an agency that had the opportunity to contact a larger in-state agency (of its type). The next table reports analyses using the expanded version (any in-state named) of the state choice variable. If anything, results were a bit more dramatic than for the first definition of the variable.

Table 3.1.1.4 Dependent Variable: Any In-state (1) or No In-state (0) Response to Question 1; State Agencies Excluded

	Model 1	Model 2	Model 3
Intercept	9.152	2.094	2.915
Log Population	-0.521 (0.195)**		-0.014 (0.249)
City Agency	-1.275 (0.824)		-0.699 (0.887)
Largest of Type in State		-2.381 (0.487)**	-2.385 (0.602)**
-2xLL	208.256	192.637	191.851
N	258	258	258

3.1.2. Type of Agency Contacted

We also studied the type (city, county, or state) of agency contacted most frequently by the responding agency (again using first listed when multiple contacts were given). In particular we examined whether the most frequently contacted was of the same type as the responding agency. The table below gives results for the dependent variable of same or different type. Again the analysis included only agencies that named a contact in Question 1.

Table 3.1.2.1 Dependent Variable: Same (1) or Different (0) Type in Response to Question 1

	Model 1
Intercept	-6.668
Log Population	0.486 (0.191)*
City Agency	1.920 (0.563)**
State Agency	2.378 (1.167)*
-2xLL	313.570
N	279

The results seem to indicate that homophily on type was more characteristic of larger agencies' ties, as larger agencies were more apt to contact an agency of the same type. It may be that larger agencies saw their problems as less general, and thus felt more need to contact an agency of the same type. However the estimated magnitude of this effect was not so great: a 10% increase in population led to 4.7% greater odds of a same type contact. The tendency toward same type contact was greatest for state agencies, who likely did not see county or city agencies as useful resources for their own planning issues. Estimated odds that a city agency's most frequent contact was another city agency were almost 7 times the estimated odds that a county agency's most frequent contact was another county agency. While this could indicate structural differences between the types of agencies, it may also reflect a situation in which there are more nationally prominent large city agencies than nationally prominent large county agencies.

As before, it was valuable to repeat this analysis with state agencies excluded, both to see whether the presence of state agencies distorted results and to permit some other interesting variables to be included. Table 3.1.2.2 gives results for city and county agencies only. The variable "same state" indicated whether the named agency was from the same state as the responding agency.

Table 3.1.2.2 Dependent Variable: Same (1) or Different (0) Type in Response to Question 1; State Agencies Excluded

	Model 1	Model 2	Model 3
Intercept	-7.276	-9.315	-9.870
Log Population	0.533 (0.198)**	0.627 (0.204)**	0.675 (0.221)**
City Agency	1.993 (0.573)**	2.243 (0.596)**	2.304 (0.607)**
Same State		0.871 (0.365)*	0.820 (0.374)*
Largest of Type in State			-0.349 (0.602)
-2xLL	304.520	298.870	298.541
N	258	258	258

Results for Model 1 were much like those in Table 3.1.2.1. In Model 2, the additional variable "same state" had a statistically significant effect. This result indicates that responding agencies' most frequent contact was more likely to be of the same type when it was from the same state. (Estimated odds that it was the same type were more than twice as large when the contact was from the responding agency's state than when it was not.) This could mean that if an agency's ties were homophilous on one dimension, they tended to be homophilous on others as well. Model 3 did not significantly improve on Model 2. Because contacts could be out-of-state, there was not an obvious implication for contact type of the responding agency's being the largest of its type in the state.[3]

We also examined the "at least one named" variant of the "same type" dependent variable. Table 3.1.2.3 reports results with state agencies excluded. Results were quite similar to those based on the first named agency, although with a larger impact of the state-homophily variable when defined as "at least one in-state named".[4]

Table 3.1.2.3 Dependent Variable: At Least One of Same (1) or All of Different (0) Type Named in Response to Question 1; State Agencies Excluded

	Model 1	Model 2	Model 3
Intercept	-7.950	-10.457	-10.116
Log Population	0.600 (0.215)**	0.709 (0.222)**	0.679 (0.240)**
City Agency	2.143 (0.591)**	2.424 (0.618)**	2.385 (0.629)**
At Least One Same State		1.170 (0.397)**	1.207 (0.415)**
Largest of Type in State			0.217 (0.685)
-2xLL	281.471	272.985	272.883
N	258	258	258

3.1.3 Population of Contacted Agency

Above we commented on the overall tendency to name larger agencies. (Of the 220 city or county agencies that named another city or county agency first for Question 1, 161 named a larger population agency.) We conducted analyses to see if agency characteristics have any systematic impact on the choice of a larger or smaller agency. One might, for example, expect that larger population responding agencies were less likely to name a larger contact, simply because there would have been fewer larger agencies available as potential alters than would be the case for smaller responding agencies. On the other hand, because the set of potential alters included all American police departments, it could be that this structural constraint would affect only a very few of the largest agencies, and would not appear as a general feature of the data. The table below gives results from this analysis for the first named agency in Question 1.

Table 3.1.3.1 Dependent Variable: Larger (1) or Smaller (0) Agency in Response to Question 1; Includes City or County Agencies that Named a City or County Agency

	Model 1	Model 2	Model 3	Model 4
Intercept	3.138	1.947	2.277	4.298
Log Population	-0.232 (0.182)		-0.164 (0.205)	-0.243 (0.216)
City Agency	0.690 (0.559)		0.789 (0.576)	0.576 (0.597)
Same State		-0.954 (0.596)		-0.967 (0.607)
Largest of Type in State		-1.159(0.627)#	-0.425 (0.582)	-0.873 (0.669)
-2xLL	250.756	251.524	250.232	247.347
N	220	220	220	220

In these models, none of the estimated effects reach the usual “p < .05" standard for statistical significance. In Model 2, the respondent’s being its state’s largest agency of that type had the expected impact of reducing the probability of naming a larger agency, and the estimate was quite large (in absolute value), but the statistical significance was borderline. Naming an alter in the same state should have had a similar structural impact, and the estimate reflected that, but the associated p-value was somewhat above .10. The estimated parameters for population had the expected sign, but were not statistically significant. The results were thus suggestive of the expected structural effects, but not conclusive given non-significance of key parameters.

In an attempt to clarify these findings a bit, we repeated the analysis with county agencies (as well as state agencies) excluded. Results are shown in Table 3.1.3.2; note that the “city type” variable was no longer meaningful, as the analysis was based on city agencies only.

Table 3.1.3.2 Dependent Variable: Larger (1) or Smaller (0) Agency in Response to Question 1; Includes City Agencies that Named a City or County Agency

	Model 1	Model 2	Model 3
Intercept	3.698	1.865	4.937
Log Population	-0.221 (0.192)		-0.254 (0.233)
Same State		-0.785 (0.598)	-0.910 (0.608)
Largest of Type in State		-1.012 (0.653)	-0.738 (0.698)
-2xLL	227.560	225.972	224.787
N	203	203	203

Results were not much different than in the previous analysis, so the findings there do not seem to have been a result of the inclusion of the (relatively few) county agencies.

We also repeated the analysis with the more liberal ("at least one larger") definition of the dependent variable, with all responses to Question 1 examined rather than only the first. Table 3.1.3.3 presents those results, again restricted to city or county agencies and, now, those that named at least one city or county agency in Question 1.

Table 3.1.3.3 Dependent Variable: At Least One Larger (1) or All Smaller (0) Named in Response to Question 1; Includes City or County Agencies that Named at Least One City or County Agency

	Model 1	Model 2	Model 3	Model 4
Intercept	3.060	4.771	1.568	3.576
Log Population	-0.233 (0.182)	-0.321 (0.199)	-0.116 (0.203)	-0.200 (0.214)
City Agency	1.050 (0.540)#	0.901 (0.559)	1.251 (0.564)*	1.122 (0.581)#
Same State		-0.599 (0.535)		-0.989 (0.609)
Largest of Type in State			-0.778 (0.586)	-1.232 (0.674)#
-2xLL	234.943	233.594	233.241	230.222
N	226	226	226	226

Comparing this table to Table 3.1.3.1, this version of the dependent variable resulted in a larger (and borderline statistically significant) estimated city/county difference. Again the estimated b's themselves seemed substantively reasonable, but many did not achieve statistical significance.

3.2 Most Frequently Contacted and Most Frequently Contacting Agencies

Our analyses thus far have focused on Question 1 (the most frequently contacted agency). In this section we will also examine Question 6 (the agency contacting the responding agency most frequently). Comparison of responses to these questions would seem to give some insight into the extent of symmetry (reciprocity) of ties in the police agency network. The extent of symmetry is in general an important structural property of social networks, and is interesting to investigate for the police network. The discussion thus far may suggest substantial asymmetry, as we have noted the apparent tendency of agencies to contact larger agencies. If this tendency is widespread, there should be many instances of a smaller agency A contacting the larger agency B, but relatively few cases of a larger agency B contacting the smaller agency A. The situation is complicated, of course, by other features of the data discussed above that indicate homophily on such dimensions as state and type. It would therefore be desirable to get some direct evidence on how much symmetry (reciprocity) characterizes the agency network.

However for several reasons the comparison of responses to Questions 1 and 6 was not ideal for assessing the extent of symmetry. As discussed above, the survey instructions for each question were to name only one agency. Our intuitive notion of reciprocity is probably something like "the frequency with which agency A contacts agency B is roughly the same as the frequency with which agency B contacts agency A". This is not quite the same as what we can say in an instance in which the same agency is named in Questions 1 and 6. That situation can be described as "agency A contacts B more often than it does other agencies, and agency B contacts agency A more than other agencies contact A". This could depart in a number of ways from the intuitive idea of symmetry. If, as seems likely, agencies differ in their propensity to send (contact) or receive (be contacted) ties, the actual frequency of contact in the two directions could differ a great deal even when the same agency is named in Questions 1 and 6. Likewise, the frequency with which A contacts B could be the same as the frequency with which B contacts A without both (or either) being the "most frequent" such contacts.

It might seem better to use only responses to Question 1, but recall that the data represent only a sample of American agencies, so there will be many instances in which an agency named in Question 1 is not itself one of the respondents to the survey. And as before there is the issue of how to take advantage of cases in which responding agencies named more than one alter for Question 1 or 6 without implicitly assuming that agencies naming only one genuinely had only one contact. These concerns certainly do not mean it is worthless to compare responses to Questions 1 and 6. But they do mean that we need to conservative in interpreting the meaning of results for the larger question of symmetry, and we will present only simple descriptive analyses.

Restricting attention to those responding agencies (of any type) naming city, county or state agencies for both Question 1 and Question 6 left 180 cases. In 42 of them, the same agency was named first for both questions. It appeared, then, that subject to all the caveats just discussed, there may have been relatively limited symmetry of ties in the police agency network. This supports the expectation of little symmetry outlined above, but again the data were not perfectly suited to this question. The large majority (37) of the 42 responding agencies that named the same alter for Questions 1 and 6 were city agencies, leaving only 5 county or state agencies, so it was not reasonable to divide the 42 cases into city, county and state respondents and compare the types of agencies named by each. Looking at responding cities only, for 30 of the 37 cities the named agency was another city agency.

As population size may be a source of asymmetry, it is interesting to compare population sizes for respondents with those of alters named in Questions 1 and 6. Rather than using the population of the first listed agency for a question, we examined the largest population among all agencies named by the respondent for a particular question. Sometimes the first listed did not have the largest population among all agencies named by a respondent, but in fact usually it did, particularly because many agencies followed the instructions by naming only one alter for each question. In 150 of these 180 cases (83%), the first agency named in Question 1 had the largest population of any named in that question (this was true by default if the respondent named only one agency). For Question 6, this proportion was 91% (164 of 180). With this in mind, Table 3.2.1 summarizes the population of responding agency, Question 1 alter, and Question 6 alter.

Table 3.2.1 Pattern of Population of Responding Agency, Most Frequently Contacted (Question 1) and Most Frequently Contacting (Question 6) Agencies.

R = responding agency's population
Q1 = maximum population of agencies named as "most frequently contacted"
Q6 = maximum population of agencies named as "most frequently contacting"

Pattern	Frequency	(%)
Q6 < R < Q1	63	(35%)
R < Q6 < Q1	46	(26%)
R < (Q1 = Q6)	24	(13%)
Q6 < Q1 < R	16	(9%)
(Q1 = Q6) < R	13	(7%)
Q1 < R < Q6	10	(6%)
Q1 < Q6 < R	4	(2%)
R < Q1 < Q6	4	(2%)

The modal pattern squared with a population-based asymmetry: the agency contacting the respondent most frequently was smaller than the respondent, and the agency that the respondent contacts most frequently was larger than the respondent. (We are speaking a bit loosely here, as the strict interpretation is based on the maximum population definition.) Perhaps cases with the pattern R < (Q1 = Q6) should also be regarding as fitting;[5] then about half the cases fit this expected pattern. Still, many cases departed from the expected pattern in some way. Perhaps the clearest feature of the data was for the maximum population given for Question 1 to exceed the maximum population given for Question 6. That occurred in 125 of 180 (69%) of cases, with these two populations equal in another 37 (21%). This seems quite consistent with the image of ties flowing from smaller to larger agencies. Again note, however, that the structure of the data left room for alternatives. When a responding agency named an alter as the agency that contacted it most frequently, this did not necessarily mean that the alter, had it been surveyed, would have named the (present) responding agency as the one it contacted most frequently. So these data were suggestive of population-based asymmetry, but interpretation should not go further.

3.3 *Contacts in Specific Domains*

Question 1 sought the agency that the respondent contacts in general most frequently. Question 10 supplemented this by asking for the most frequent contact in a number of specific domains (domestic violence, deadly force, gangs, community policing, problem-oriented policing, drug enforcement strategy, civil liability, labor relations, personnel administration, accreditation, police traffic services). The availability of these data suggest a number of possible interesting analyses. Here we will report on the extent to which agencies named as general contacts were also named for the specific domains, on differences in the types of agencies named for the different domains, on the question of whether the data reveal "expert" departments, and on the similarity of the domains themselves. Before discussing these analyses, it is important to note that many agencies that responded to Question 1 did not respond to all or part of Question 10. Of 277 agencies with a decipherable response to Question 1, only 73 (26%) responded to all 11 parts of Question 10. 28 (10%) did not respond to any part of Question 10, and another 68 (25%) responded to fewer than half of Question 10's items. Some of the non-response may be because certain items in Question 10 seem less relevant to state than to municipal or county agencies. But even if restricted to the 255 city or county agencies responding to Question 1, only 68 (27%) responded to all parts of Question 10, and 27 (11%) did not respond to any item in

Question 10.

3.3.1 General and Specific Contacts

Focusing on the 256 city or county agencies that responded to Question 1, we can examine the extent to which the agency named in Question 1 was also named in different parts of Question 10. Table 1 presents information on this, indicating how often the first named agency in Question 1 was named at all (not necessarily first) in Question 10's items.

Table 3.3.1.1 Appearance by "Most Frequently Contacted Agency" in Lists of Agencies Contacted in Specific Domains; City or County Respondents Only

Domain	Most Frequently Contacted		No Response
	Appeared	Did Not Appear	
Domestic Violence	82 (32%)	87 (34%)	87 (34%)
Deadly Force	95 (37%)	80 (31%)	81 (32%)
Gangs	65 (25%)	130 (51%)	61 (24%)
Community Policing	69 (27%)	118 (46%)	69 (27%)
Problem-oriented Policing	66 (26%)	104 (41%)	86 (34%)
Drug Enforcement Strategy	55 (21%)	113 (44%)	88 (34%)
Civil Liability	80 (31%)	50 (20%)	126 (49%)
Labor Relations	72 (28%)	58 (23%)	126 (49%)
Personnel Administration	89 (35%)	52 (20%)	115 (45%)
Accreditation	75 (29%)	72 (28%)	109 (43%)
Police Traffic Services	80 (31%)	98 (38%)	78 (30%)

Clearly most agencies were not simply rewriting the response to Question 1 for the different items of Question 10. Likely that did happen in some instances, but for each part there were a large number of real responses that did not include the most frequently contacted agency, and many non-responses. It seems that Question 10 indeed generated distinct information, although empirically responses there can overlap with responses to Question 1. The variation across items in the appearance of the most frequently contacted agency may help describe the domains themselves; we will address that below.

3.3.2 Agency Types in Different Domains

Earlier we discussed the apparent homophily on agency type in responding agencies' choices of network alters. Data on choices made in the different domains can help illuminate this further. Are tendencies toward homophily on type stronger or weaker in different domains? The subtables of Table 3.3.2.1 give cross-classifications of responding agency's type and first named alter's type for the 11 parts of Question 10. In each subtable, only city, county or state agencies that gave a decipherable response in the particular domain are represented. The subtables are not square because no type "other" agencies were among the respondents, and the row and overall totals in each subtable differ due to varying rates of non-response to different parts of Question 10. Note also that a subtable includes all non-tribal agencies responding to that part of Question 10, whether or not they responded to Question 1. The later items seemed to have more non-response; that could indicate questionnaire fatigue, although the last item was an exception. It could instead be that agencies were genuinely less apt to seek advice in some domains than others.

Table 3.3.2.1 Cross-classification of Responding Agency Type with First Named Agency, for Specific Domains

A: Domestic Violence (N = 201)

		First Named			
		City	County	State	Other
	City	131	21	16	3
Respondent	County	9	6	0	0
	State	8	0	6	1

B: Deadly Force (N = 215)

		First Named			
		City	County	State	Other
	City	133	26	12	8
Respondent	County	7	7	2	1
	State	3	1	12	3

C: Gangs (N = 255)

		First Named			
		City	County	State	Other
	City	162	36	13	5
Respondent	County	11	7	0	0
	State	13	0	8	0

D: Community Policing (N = 236)

		First Named			
		City	County	State	Other
	City	184	14	2	1
Respondent	County	13	5	0	0
	State	8	1	8	0

E: Problem-oriented Policing (N = 210)

		First Named			
		City	County	State	Other
	City	162	11	3	3
Respondent	County	8	6	1	0
	State	6	0	10	0

F: Drug Enforcement Strategy (N = 211)

		First Named			
		City	County	State	Other
	City	80	25	19	50
Respondent	County	5	5	0	7
	State	1	0	9	10

G: Civil Liability (N = 157)

		First Named			
		City	County	State	Other
	City	96	16	6	11
Respondent	County	7	6	1	0
	State	0	0	10	4

H: Labor Relations (N = 154)

		First Named			
		City	County	State	Other
	City	99	18	5	6
Respondent	County	7	6	1	0
	State	1	0	11	0

I: Personnel Administration (N = 169)

		First Named			
		City	County	State	Other
	City	112	18	6	4
Respondent	County	6	8	0	0
	State	2	0	13	0

J: Accreditation (N = 179)

		First Named			
		City	County	State	Other
	City	116	24	9	0
Respondent	County	3	8	1	2
	State	2	0	14	0

K: Police Traffic Services (N = 226)

		First Named			
		City	County	State	Other
	City	114	16	58	1
Respondent	County	6	5	7	0
	State	1	0	18	0

All the subtables seem to indicate a tendency for agencies to seek advice from agencies of the same type. But the different N's make the subtables somewhat difficult to comprehend, and the fact that a large majority of responding agencies were city departments also hinders simple inspection of the subtables. It is also hard to know what to make of situations like that in police traffic services, in which many city and county agencies named a state agency for that domain. Note that drug enforcement strategy was somewhat special, because many responding agencies named the Drug Enforcement Agency (classified as "other") as their contact in this domain.

To examine different tendencies toward type-homophily in the different domains, we fit simple log-linear models to the subtables (with the column for "other" excluded, leaving 3x3 subtables). The model of independence says that the responding agency's type was independent of the named agency's type. The model cell (i, j)'s count may be written as

$$\log m_{ij} = \lambda + \lambda_{1(i)} + \lambda_{2(j)}.$$

It seems clear that independence does not characterize the subtables, but the model is still a useful starting point. Of more interest is what Marsden (1981) called the "constant inbreeding" model. This model also arises in other contexts, but it is often applied to square tables representing some kind of social interaction (such as marriage or friendship, to take two common examples). The model suggests that all groups (rows and columns of the table) have the same tendency toward intragroup interaction, but that independence characterizes intergroup interaction. The model extends independence with one parameter representing this tendency toward within-group interaction. The parameter distinguishes cells on the diagonal of the table:

$$\log m_{ij} = \lambda + \lambda_{1(i)} + \lambda_{2(j)} + \lambda_D I_{i=j},$$

where $I_{i=j}$ is an indicator that equals one if i = j (diagonal cells) and equals zero otherwise.

It is natural to next consider what Marsden (1981) calls "differential inbreeding", but in many of the tables, the pattern of zero cells prevents us from assessing its fit, and in any case this model would use all but one degree of freedom in each subtable. So we considered an extended constant inbreeding model, in which an additional parameter was estimated to capture any tendency toward city agencies making out-group choices of county (rather than state) and county agencies making out-group choices of city (rather than state) agencies. Adding this parameter does, however, result in the count of state agencies naming state agencies being fit exactly. This is an unfortunate byproduct of extending the model in such a small table with so few available degrees of freedom.

Table 3.3.2.2 reports on the fit of these models in the different domains. The likelihood ratio G^2 statistic is a type of chi-square statistic; in these 3x3 tables, degrees of freedom are 4 for independence, 3 for constant inbreeding, and 2 for extended constant inbreeding. Asterisks indicate if the model "fit" at the 0.05 (*) level; the implicit null hypothesis is that the model fits, so a small p-value leads to rejecting the hypothesis that this model fits, and an asterisk indicates that p>0.05. If the model does not fit, this is interpreted as the model not adequately describing the relationship between responding and named agency type. For the extended constant inbreeding model, the estimated values of the inbreeding and city-county parameters (and their standard errors) are also given. The pattern of zero cells meant that the fit of extended constant inbreeding could not be assessed for civil liability.

Table 3.3.2.2 Fit of Independence and Constant Inbreeding Models to Subtables of Table 3.3.2.1

Domain	Indep.	Constant Inbreeding	Extended Constant Inbreeding		
				Parameters	
	G^2	G^2	G^2	Inbreeding	City-County
Domestic Violence	27.228	11.213	5.740	1.586 (0.343)	0.998 (0.429)
Deadly Force	46.059	8.340	0.217*	1.913 (0.323)	1.105 (0.401)
Gangs	28.052	16.261	10.163	1.203 (0.268)	0.874 (0.354)
Community Policing	43.068	12.057	0.668*	2.351 (0.431)	1.569 (0.508)
Problem-oriented Pol.	57.589	8.814	2.638*	2.279 (0.362)	1.112 (0.460)
Drug Enforcement Strat.	32.646	13.137	4.543	2.083 (0.545)	1.550 (0.619)
Civil Liability	55.913	18.116	------		
Labor Relations	56.080	17.287	0.709*	2.836 (0.564)	2.074 (0.621)
Personnel Administration	70.009	15.588	3.174*	2.654 (0.435)	1.634 (0.507)
Accreditation	69.344	9.905	2.151*	2.503 (0.416)	1.307 (0.500)
Police Traffic Services	38.901	4.837*	0.596*	1.930 (0.521)	1.063 (0.596)

As expected, independence did not seem to characterize any of the subtables; in all cases, the responding agency's type did appear to be associated with the named agency's type. Constant inbreeding gave, in all domains, a significant improvement in fit over independence, though it "fit" in only one domain (this result did not change when Pearson's X^2 was used instead of G^2). That is, adding a parameter for the tendency toward in-group choices significantly improved fit, but was not (except for police traffic services) sufficient to describe the association between responding and named agency type. In most domains extended constant inbreeding did in fact "fit" the data. The estimated inbreeding parameters were in most cases very large, although the city-county parameters were large also, suggesting that the distinction between city and county agencies was not as great as the distinction between either and state agencies.

To illustrate the meaning of these parameters, let us look at the problem-oriented policing domain (one of the domains in which the extended constant inbreeding model fits). One interpretation is based on ratios of odds of different types being chosen by different responding types. One sort of odds ratio is: (odds of an agency of type i contacting type i vs. contacting type j) / (odds of agency of type j contacting i vs. contacting j). This odds ratio indicates the extent to which the two types favor same-type over cross-type contacts, and is related to the inbreeding parameter. But the presence of the city-county parameter is a complication, because it means this odds ratio differs when i and j refer to city and county than when state is involved. If i and j are city and county, this odds ratio is given by the exponentiation of twice the difference between the inbreeding and city-county parameters. For the problem-oriented policing subtable, this is $\exp\{2(2.279-1.112)\} = \exp\{2.334\} = 10.32$. On the other hand, if state is involved, this is simply the exponentiation of twice the inbreeding parameter. Here, this is $\exp\{2(2.279)\} = \exp\{4.558\} = 95.39$, a vastly higher figure. The relative tendency toward in-group contact appeared much stronger when examining city and state or county and state than when examining city and county. In an important way, therefore, the city and county types were more similar to each other than either was to state (although still there was a strong tendency toward in-group contact when looking at city and county). From the parameters in Table 3.3.2.2 for domains in which the extended constant inbreeding model fit, the city/county similarity seemed least for problem-oriented policing and accreditation, and relatively consistent across other domains.

Notice that the constant inbreeding model "fit" in the police traffic services domain. It is best not to "overfit", by adding more parameters to a model that already fits, so for this domain it is preferable to interpret constant inbreeding. The estimated inbreeding parameter was 1.306, which still suggests substantial tendencies toward in-group choice in this domain (under the sort of odds ratio calculation given above). But recall that the subtable for this domain appeared to show many out-group choices. There were many instances of city agencies and county agencies naming state agencies, and this helps illustrate a caution in interpreting these models. The many choices of state agencies by city and county meant a large total in the state column. And the odds ratio interpretations we have discussed are (in effect) net of the subtable's marginal totals. Taking that large column total as given, there did not seem to be an unusually large number of cities naming state agencies. With these log-linear models, the marginal totals themselves are not the object of the analysis. Often that is reasonable, but there are cases (such as with the police traffic services subtable) in which features of the marginals seem substantively important. We do not explore them here, but there are models that investigate marginal totals as well as odds ratios net of margins (Sobel, Becker & Minick, 1998). In the standard log-linear framework, however, we need to realize that there may be interpretable information in the margins that we are not accessing.

Some of our interpretation has focused on the similarity of the different types of agencies. A more direct way to investigate this is through correspondence analysis of the subtables.

Correspondence analysis is a technique for analyzing the association between row and column variables in a table. There are many technical details, but in brief, the analysis extracts a number of “dimensions” from the table. In each dimension, there is a score for each row category, and a score for each column category. These scores can be plotted, so that each row category (or column category) is represented by a point in the plot. Two row points are nearby in the plot if the cases in those rows are similarly distributed into the columns of the table (and likewise for column points). See Weller and Romney (1990) for an accessible non-technical introduction.

In our setting, correspondence analysis of the subtables would provide scores for the responding agency types, so we could, for instance. assess how similar the pattern of choices by city agencies was to the pattern of choices by county agencies. (We would also have scores for the named agencies, although those are perhaps of less direct interest here.) The scores could be plotted, but here we will focus only on the first dimension scores, and will thus simply report them in a table rather than a plot. Table 3.3.2.3 gives responding city, county, and state agency scores for the various subtables.

Table 3.3.2.3 Correspondence Analysis Scores for Responding Agency Types, Subtables of Table 3.3.2.1

Domain	City Type	County Type	State Type
Domestic Violence	-0.091	-0.468	1.450
Deadly Force	-0.181	0.042	1.672
Gangs	-0.070	-0.474	1.128
Community Policing	-0.162	-0.199	2.126
Problem-oriented Policing	-0.199	-0.018	2.241
Drug Enforcement Strategy	-0.102	-0.307	1.146
Civil Liability	-0.204	-0.254	2.137
Labor Relations	-0.228	-0.125	2.573
Personnel Administration	-0.213	-0.423	2.387
Accreditation	-0.211	-0.241	2.176
Police Traffic Services	-0.129	0.087	1.199

The general pattern seems consistent across the domains: city and county were relatively similar, and state was quite distinct. (The difference between the city and county scores was small relative to the difference between either and the state score.) A difference between the contacts made by city and county agencies was apparent in most of the domains (domestic violence, deadly force, gangs, drug enforcement strategy, and police traffic services) but even in these domains the city-county difference was substantially smaller than the city-state or county-state difference. (The city and county scores seemed fairly different for problem-oriented policing and personnel administration, but the large state scores suggest that the relative difference between city and county was not so great in those domains.) In general city and county agencies appeared similar, but not identical, and state agencies quite distinct in the types of agencies contacted.

3.3.3 Agency Expertise

Question 10 may also give some insight into the perceived expertise of different agencies in different domains. It seems reasonable that agencies would have sought specialized advice from others whom they perceived as offering particular expertise for the issue at hand. Therefore agencies that were seen as offering domain-specific expertise should be named often in that part of Question 10; as Weiss (1998a) noted, frequently named agencies for a part of Question 10 are likely those with perceived expertise in that domain. This interpretation must be made cautiously, however. We have already noted the influence of geography (the tendency toward in-state) and agency size and type on choice of contacts. Given the makeup of the sample of responding agencies, an apparent "expert" may have simply been in position to be named by many respondents due to these factors, rather than having been perceived as especially expert in a domain. It would be better to standardize the number of times an agency is mentioned in a domain of Question 10, but it is not clear what would be the best technical approach to doing that.

We took the simplest possible approach: we identified "relative expertise" by comparing the number of times an agency was mentioned as the most frequent general contact (Question 1) with the number of times it was mentioned in a particular part of Question 10. Because the influences of geography and agency characteristics should have operated in both Question 1 and Question 10, when an agency was named more often in a domain of Question 10 it was likely because of perceived expertise in that domain. Note, though, that this does not mean that an agency that was frequently named in both Question 1 and a part of Question 10 did not have genuine expertise in that domain. Rather the data do not allow us to separate specific domain expertise from general popularity as a network contact. We must therefore be clear in interpreting this analysis as indicating relative, not absolute, expertise.

Table 3.3.3.1 shows city or county agencies identified as "relative experts" in each domain. The Table reports all agencies with at least 3 more mentions in a part of Question 10 than in the general Question 1 (numbers in parentheses give the difference between the number of mentions in the domain and the number in Question 1). Note that state and national agencies were excluded, including some with obvious expertise. For example, the Drug Enforcement Agency was named 66 more times in the drug enforcement strategy domain than it was as a general most frequent contact. The California Highway Patrol was named 18 more times for police traffic services than as a general most frequent contact. Such agencies do not appear in the Table.

Table 3.3.3.1 "Relative Experts": City or County Agencies Named More Often in a Domain than as General Contacts

Domain	Agencies
Domestic Violence:	Minneapolis PD, Quincy MA PD (3)
Deadly Force:	Los Angeles PD (7)
Gangs:	Los Angeles PD (30), Chicago PD (10), Los Angeles Sheriff (5), Boston PD (4), Detroit PD, San Antonio PD, Providence RI PD (3)
Community Policing:	San Diego PD (12), Portland OR PD (9), Madison WI PD (7), St. Petersburg PD (5), Baltimore County PD (4), N. Miami Beach PD (3)
Problem-Oriented Policing:	San Diego PD (24), Newport News PD (8), Madison WI PD (4)
Drug Enforcement Strategy:	Miami FL (6)
Civil Liability:	none with at least 3 more
Labor Relations:	none with at least 3 more
Personnel Administration:	none with at least 3 more
Accreditation:	Salisbury MD PD (4), Tempe AZ PD (3)
Police Traffic Services:	none with at least 3 more

It appears that "relative experts" were more apt to emerge in domains that are more exciting, or at least more interesting to the general public (although some emerge in accreditation also). Madison stands out as a rather small department that had some reputation in community policing and related areas, although San Diego appeared to be the prime source in these domains. It is interesting that LAPD received such attention in the gangs domain, as that probably agrees with what the average American would have gleaned from television.

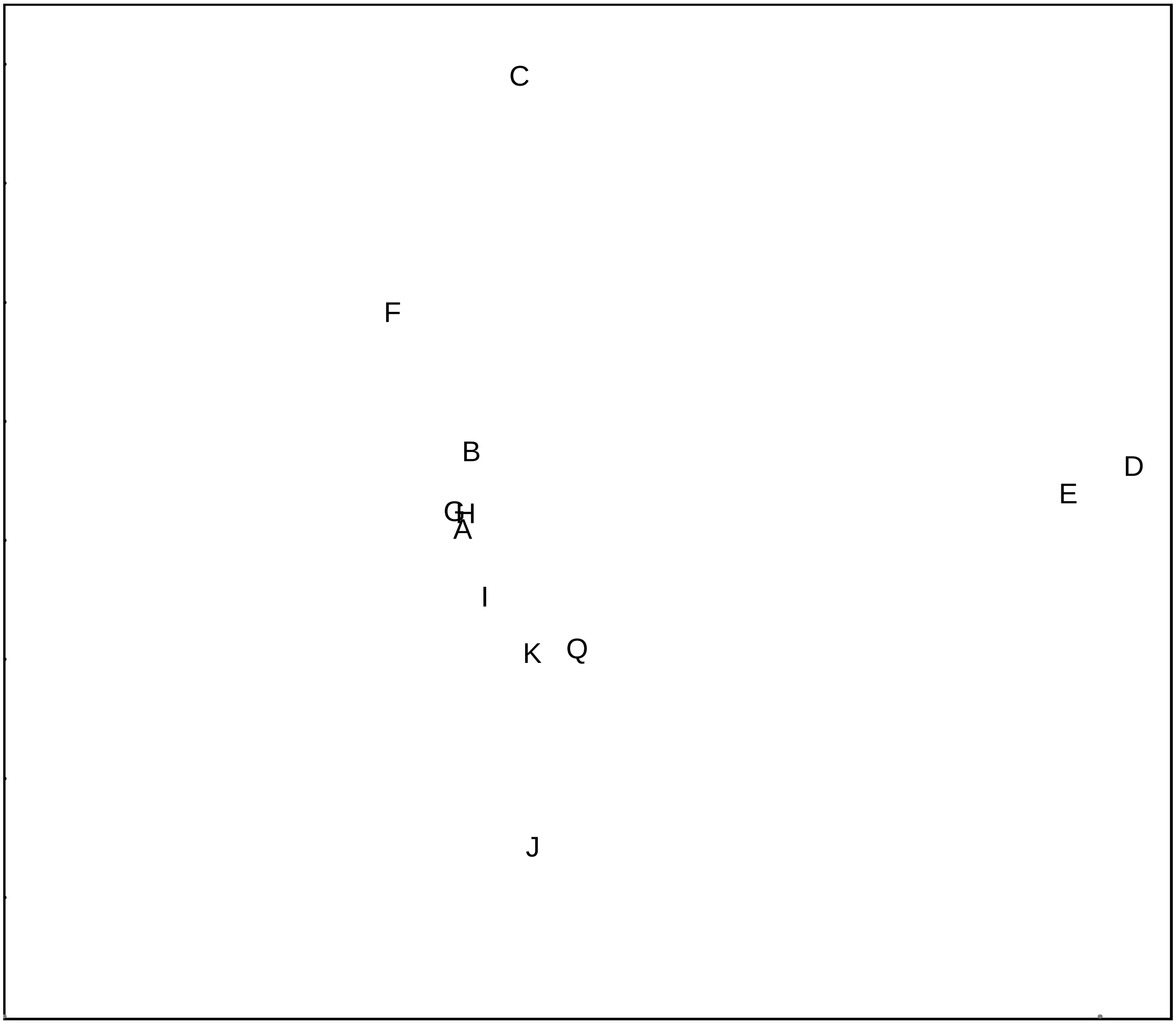
3.3.4 Similarity of Domains

As a final analysis of Question 10, we used the responses to try to assess the inherent similarity of the various domains. We proceeded from the idea that if two domains were similar, similar agencies should have been popular contacts in each. (This is akin to the idea that two groups are similar to the extent that they share members.) We constructed data on the overlap in the alters that each responding agency named for the different domains. This would be straightforward if each agency named at most one alter in response to a question, but, as we have noted many times, many named multiple agencies. Then there are many different ways to conceive of overlap. We counted "matches" and "non-matches" as follows. Suppose for domain 1 a responding agency named alters A, B, C, and D, and for domain 2 the agency named C, E, F, and G. The agency then named seven different alters in total, and one appeared in both lists. We took this as generating one match and six non-matches. Again, there are alternative ways to count, but the end result would probably be similar for any reasonable counting method.

For each pair of domains, we made this calculation for each responding agency and then summed the number of matches and non-matches. We then constructed a symmetric 12x12 table in which cell (i, j) gave the number of matches between domain i and domain j, divided by the sum of matches and non-matches between the two domains.[6] There were only 11 domains from Question 10, but for comparison we also included Question 1 as, in effect, an additional "general" domain. We then submitted this table to correspondence analysis.[7]

Figure 3.3.4.1 shows the plot of domain scores from the correspondence analysis. The first two dimensions are shown. In fact more dimensions may be required to adequately represent similarities and differences between domains, as the first two dimensions accounted for only 33% of the association in the table. However this assessment may be a bit pessimistic, as interpoint distances in this plot correlated 0.73 with interpoint distances in the (imaginary) plot using all 11 dimensions possible from the table. (See Roberts [2000] for a discussion of this sort of correlation.) In any event, we interpreted the two-dimensional plot shown in the figure. A pair of domains should be nearer in the plot if they were more similar (as judged by the proportion of matches described above). Domains are labeled with the letters from Table 3.3.2.1. The point representing the general Question 1 is labeled Q.

Figure 3.3.4.1 Domain Scores, from Correspondence Analysis of Table Giving Proportions of Matches.



The first dimension (horizontal) seemed to mainly distinguish the two community policing-related domains from the others; it is not surprising that the two community policing-related domains appear quite similar. The second dimension (vertical) appeared to distinguish among the non-community policing-related domains. Accreditation seemed rather different from other domains; this is perhaps consistent with the "relative experts" revealed in this domain being smaller and less prominent departments than in other domains. It is not surprising that gangs and drug enforcement strategy appeared somewhat distinct from the more bureaucratic domains, although the position of domestic violence is harder to interpret. The bureaucratic domains appeared relatively similar to the general domain (Question 1).

3.4 Influences on Choice of Specific Contacts

To this point, our analyses have focused on such questions as whether a named contact was from the responding agency's state, or whether it was of the same type as the responding agency. These analyses are very informative, but do not address the specific choice of an alter. That is, there were typically many agencies of the respondent's type in its home state—what factors influenced the specific choice it made? Agency size is one factor we have discussed already, but even if there were a tendency toward contacting larger agencies, many times there were multiple larger agencies to choose from in the state. Our next analyses address this sort of choice. Along with the agency characteristics of type and population, we considered geographic distance between the respondent and potential alters.

3.4.1 <u>In-state Most Frequently Contacted</u>

We first studied the 199 agencies that named an in-state city or county alter for Question 1 (most frequently contacted). There were several steps in constructing the data set for this analysis. For each of these agencies, we generated a list of their state's city and county departments from CSLLEA; we excluded special agencies, even when they were affiliated with a city or county government. We then looked at the CSLLEA designations for patrol and response to calls as responsibilities of each department. If a city agency reported either of these responsibilities, we included it in the set of potential alters. County agencies that reported patrol (or patrol and response to calls) were included, while those reporting only response to calls were excluded. We also supplemented our lists with any known omissions from CSLLEA.

Of course many states have lots of very small agencies. Given the various results concerning population discussed above, we thought it unrealistic to consider a very small agency as a potential alter for a very large one. (Recall that for Question 1 the smallest ratio of named agency's population to responding agency's population was 0.074. That seems very small, but for a responding agency with population 1,000,000 that would correspond to a named agency population of 74,000. Most states have a large number of agencies with populations below that.) We decided that we would view agencies with population ratio (to the responding agency's population) of at least 0.10 (for city respondents) or 0.05 (for county respondents) as the set of potential alters. With these rules, the 199 responding agencies gave, all together, 36,840 potential alters, so the data set for the analysis had N = 36,840. Even though the lists were generated from the responding agencies, each observation in the new data set referred to a potential alter. It is convenient, however, to think of the observations as grouped in 199 blocks, each associated with one of the responding agencies.

We used logistic regression, with the dichotomous dependent variable indicating whether (1) or not (0) the potential alter had in fact been named by the responding agency on whose list of potential alters it appeared. Of course for most of the 36,840 cases, the alter was not named, but the construction of the data requires that each of the 199 blocks have at least one case with value 1 on the dependent variable. In fact, as we have said, many agencies named more than one alter, so many blocks had multiple cases with value 1 on the dependent variable. Again there is concern because many agencies could have named multiple alters had the instructions said to do so. But for this analysis we wanted to take advantage of all the named alters rather than use only the first listed.[8]

The structure of the blocks introduced one complication. It is not legitimate to view the observations within a block as independent of each other, so some accommodation for this non-independence was required. We addressed this by including a set of dummy variables to represent the blocks (there were 199 blocks, so we used 198 dummy variables). This should capture a tendency toward similarity of the observations within blocks, and permit a reasonable analysis in the presence of non-independence. Coefficients for the dummy variables were estimated in the usual way. This could be called a "fixed effects" analysis; "random effects" (Agresti, 2002) would be an alternative, but we did not pursue that here. (One motivation for random effects is to save degrees of freedom, but the 198 dummy variables were not so many relative to the 36,840 observations.) These dummy variables have the practical effect of fitting exactly the number of alters named by each responding agency, so differences in the number of choices made by different respondents should not have confounded the effects of the independent variables.

Along with the dummy variables for the blocks, we were interested in the impact of agency type, population, and geographical distance. We explored several different specifications of type; the first analysis reported here simply used an indicator of whether the potential alter was of the same type (city or county) as the responding agency. For population, we used the (logged) ratio of potential alter's to responding agency's population. To measure distance between the responding agency and the potential alters, we used the city listed for each agency in CSLLEA. Latitude and longitude coordinates were obtained for each city from resources available online from the United States Geological Survey. (Files with coordinates for all populated places are available, and individual queries are also possible at the USGS website.) We then calculated distance between the responding agency and each potential alter from the coordinates (using the haversine method). Occasionally the agency place names were confusing for smaller agencies in a large metropolitan area. For example, Dormont is adjacent to the city of Pittsburgh, Pennsylvania. Dormont is a separate municipality and has its own police force, but the listed city for the Dormont Boro Police Department is Pittsburgh. In such cases, we attempted to identify a more appropriate set of coordinates than those for the metropolitan area's main city. Because a given number of miles has a different meaning in a crowded northeastern state than in a sparsely populated western state, we used the logged rank (within the block) of each alter's distance from the responding agency rather than the distance (or logged distance) itself.

In our models, we used these three variables ("same type", logged population ratio, and logged rank of distance), the square of logged population ratio (to examine whether the effect of this variable differed for different values), and interactions between them. Table 3.4.1.1 gives summary measures (-2 x log-likelihood) for the fit of various logit models. Again, two nested models can be compared by viewing the difference in -2 x log-likelihood as a chi-square statistic (with degrees of freedom given by the difference in number of parameters, or equivalently the difference in degrees of freedom for the two models). If the chi-square gives a small p-value, the more complicated model is a statistically significant improvement over the less complicated model. Degrees of freedom used for each model reflect the intercept and the 198 dummy variables for the block effects as well as the substantively interesting variables.

Table 3.4.1.1 Fit of Logistic Regression Models to Question 1 Alter Choice Data, In-state

Independent Variables: A, B, C stand for same type, logged population ratio, and logged rank of distance, respectively. B^2 stands for logged population ratio squared, and AB, AC, and BC stand for interactions between pairs of variables.

Model	-2 x log-likelihood	df Used
1. A, B, C	1914.082	202
2. A, B, C, AB	1914.080	203
3. A, B, C, AC	1907.469	203
4. A, B, C, BC	1884.627	203
5. A, B, C, B^2	1859.498	203
6. A, B, C, B^2, AB, AB^2	1784.652	205
7. A, B, C, B^2, BC, B^2C	1824.093	205
8. A, B, C, B^2, AB, AB^2, BC, B^2C	1760.382	207
9. A, B, C, B^2, AB, AB^2, BC, B^2C, AC	1758.567	208

Balancing fit and parsimony, Model 8 (main effects, squared term for logged population ratio, interaction between same type and population, and interaction between population and distance) seemed best among the models in this set. The improvement in fit from adding an interaction between same type and distance (Model 9) to Model 8 was not statistically significant (difference in -2 x log likelihood = 1.815, 1 df, $p > 0.10$). The squared version of the population variable appeared to improve fit, so Model 5 was a more appropriate baseline than Model 1.

Table 3.4.1.2 reports on the parameter estimates in Model 8. Estimates are presented for the eight substantively interesting parameters, not the terms for the blocks or the intercept.

Table 3.4.1.2 Parameter Estimates for Model 8 of Table 3.4.1.1

Independent Variable	Estimated b (standard error)
A (Same Type)	4.083 (0.290)**
B (Logged Population Ratio)	1.135 (0.195)**
C (Logged Rank of Distance)	-0.761 (0.065)**
B^2 (Square of Logged Population Ratio)	0.417 (0.081)**
Interactions	
A x B	1.111 (0.186)**
A x B^2	-0.561 (0.069)**
B x C	-0.016 (0.057)
B^2 x C	-0.075 (0.023)**

The large sample size contributed to the small standard errors (relative to the estimates) for many of the parameters, although the Table also shows that it was possible for a particular parameter to not differ significantly from zero even with the large N. The presence of the various squared and interaction terms make interpretation somewhat difficult, because the effect of one variable depends on the level of the others, but we can try to carefully describe the results. Of course all figures are estimates, although for convenience we will not keep saying that.

For “same type” (A), we need to specify the level of logged population ratio (B). Suppose a potential alter was of the same size as the responding agency (population ratio = 1, thus logged population ratio = 0). Then the odds of this alter being named were much greater (about 59 times, from exp[4.083]) when it was the same type as the responding agency than when it was not. If the potential alter was only half the size of the responding agency (implying that logged population ratio = -0.693), this difference in odds was about 21 times (from exp[3.044]); if twice as large (logged population ratio = 0.693), the odds of being named were 98 times greater (from exp[4.584]). While this is a rather remarkable figure, note that because respondents were generally large agencies, the vast majority of potential alters were smaller. At any size of the potential alter, type appeared to be salient in the choice of contacts.

Logged population ratio appeared in interactions with the each of the other variables, so values must be specified for each to see the effect of population ratio, and the squared term means we must also specify a value of logged population ratio itself. Suppose we start from a potential alter of the same type as the respondent (A = 1), of the same size (B = 0), and the nearest potential alter (C = 0), and compare odds of being named with those when the alter was half the size (B = -0.693) of the respondent. Odds of being named would have been about 5 times (exp[1.626]) greater for the larger potential alter than for the smaller. Comparing (otherwise similar, with A = 1 and C = 0) a potential alter of twice the responding agency's size with one of the same size as the respondent, the larger would have had about 4 times greater odds of being named (exp[1.487]). If the distance rank were set to 6 (C = 1.792), these figures changed little (exp[1.670] and exp[1.403]). Had the potential alter been of different type (A = 0, and again with C = 0), the two odds ratios would have been only 1.80 (exp[0.586]) and 2.68 (exp[0.987]) respectively. In general, then, these results agree with earlier comments on the role of size—alters that were larger relative to the responding agency were more likely to be named. This tendency appeared stronger for alters of the same type as the respondent.

For the impact of distance, there was no interaction with type, but we still need to specify a value of logged population ratio. If B = 0, the odds of being named were almost 4 times greater (exp[1.364]) for an alter that was nearest the respondent © = 0) than for one that was sixth closest (C = 1.792). If B = -0.693, this figure changed little (exp[1.408]). The distance effect thus seemed to be as expected. Potential alters that were farther away from the responding agency (in the sense of rank, with more other alters that are closer) were less likely to be named. The impact of distance did not appear to be too sensitive to the level of population ratio, even though the BC interaction is shown in Table 3.4.1.1 to be statistically significant.

Noting the large estimated impact of same type, we explored this variable further. An alternative formulation of the same type variable would be to distinguish between responding city agencies naming city alters and responding county agencies naming county alters. We estimated models of the sort listed in Table 3.4.1.1 with this alternative formulation. A model with the alternative formulation and its counterpart in Table 3.4.1.1 were nested, because the model in Table 3.4.1.1 could be obtained from that with the alternative formulation by requiring that "same type: city" parameters be equal to "same type: county". Focusing on Model 8 (the most preferred in Table 3.4.1.1), the alternative formulation gave -2 x log-likelihood = 1702.102, using 210 df (because now each term involving A needs two parameters rather than one). The difference in -2 x log-likelihood of 58.280, on 3 df, suggests a significant ($p < 0.001$) improvement in fit with the alternative formulation, and would indicate that the impact of same type differed at least somewhat between city and county respondents.

We then explored a simplified alternative formulation of Model 8, in which same type mattered for city respondents but not for county respondents. The model with the simplified alternative and the model with the alternative formulation were nested (the simplified alternative obtained from the alternative by setting the "same type: county" parameters equal to zero), but the simplified alternative and the model in Table 3.4.1.1 were not nested. -2 x log-likelihood was 1704.493, using 207 df. Comparing the simplified alternative with the alternative, the alternative did not significantly improve fit (difference in -2 x log-likelihood = 2.391, 3 df , $p > 0.30$). The preferred formulation, then, appears to be one with "same type" parameters for city respondents, but not for county respondents. That is, holding population ratio and distance rank constant, odds of the alter being named were the same for the situations of {city respondent, county alter}, {county respondent, city alter}, and {county respondent, county alter}, but differed for the situation of {city respondent, city alter}. With this simplified alternative, the tendency of city respondents to name city alters was slightly stronger than that described above for the original formulation. (Parameters in the original formulation in effect averaged over many city respondents and a small number of county respondents, with the parameters essentially zero for the county respondents. Thus the estimated effects in the original formulation were close to, but somewhat less than, those for city respondents in the simplified alternative.)

3.4.2 Out-of-state Most Frequently Contacted

We conducted a similar analysis on out-of-state choices. For the 33 responding city or county agencies that named an out-of-state alter for Question 1, we constructed a set of potential alters of all out-of-state agencies with population at least 100,000 (for potential alters of type city) or at least 500,000 (for potential alters of type county). We based these figures on the fact that observed out-of-state choices were never small population agencies. This led to a total of 10,014 observations in the new data set, again with the dichotomous dependent variable indicating that the alter was named in Question 1. We used the same three factors as above, although with the simplified alternative formulation only for same type. Table 3.4.2.1 reports on -2 x log-likelihood for a variety of models. Note that the numbering of models follows that in Table 3.4.1.1, with two additional models not considered in the earlier Table.

Table 3.4.1.2 Fit of Logistic Regression Models to Question 1 Alter Choice Data, Out-of-state

Independent Variables: A, B, C stand for "same type: city", logged population ratio, and logged rank of distance, respectively. B^2 stands for logged population ratio squared, and AB, AC, and BC stand for interactions between pairs of variables.

Model	-2 x log-likelihood	df Used
1. A, B, C	679.251	36
2. A, B, C, AB	678.868	37
3. A, B, C, AC	676.079	37
4. A, B, C, BC	663.340	37
5. A, B, C, B^2	665.683	37
6. A, B, C, B^2, AB, AB^2	662.630	39
7. A, B, C, B^2, BC, B^2C	653.120	39
8. A, B, C, B^2, AB, AB^2, BC, B^2C	650.748	41
9. A, B, C, B^2, AB, AB^2, BC, B^2C, AC	643.952	42
10. A, B, C, B^2, BC, B^2C, AC	647.644	40
11. A, B, C, B^2, AC	661.752	38

There are some similarities to results in Table 3.4.1.1, but some differences also. Again the squared logged population ratio was valuable, and Model 5 was an appropriate baseline. Model 7 was again a significant improvement on Model 5. From this point, however, results were somewhat ambiguous. By the classical test (looking at differences in -2 x log-likelihood, with an assumed chi-square distribution), Models 7 through 11 were all preferred to Model 5. One criticism of the classical test is its sensitivity to sample size: with a large N, as in this analysis, there is a danger of overfitting under the classical test. The BIC statistic (Raftery, 1995) is one alternative to the classical test. Under BIC, in fact none of models 7 through 11 were, in light of the sample size, judged to improve fit sufficiently to justify their use of additional degrees of freedom.[9]

A case can be made, then, for not considering any of the interactions, as the complexity they introduce did not seem, under BIC, to be justified in sufficient improvement in fit. Absence of interaction may have been substantively more reasonable in the out-of-state data than in the in-state data, as it at least suggests a simpler decision mechanism. Of course this is highly speculative, but greater opportunity to learn about counterparts at other in-state agencies may have lead to a more complicated weighting of the factors that impact the perceived desirability of a network alter. But such speculation really goes beyond the results at hand. In any event, we will interpret the simpler Model 5 rather than any of the models with the interactions (though note that the squared term remains).

Table 3.4.2.2 Parameter Estimates for Model 5 of Table 3.4.2.1

Independent Variable	Estimated b (standard error)
A (Same Type: City)	4.650 (0.753)**
B (Logged Population Ratio)	1.584 (0.163)**
C (Logged Rank of Distance)	-0.855 (0.083)**
B^2 (Square of Logged Population Ratio)	-0.209 (0.064)**

As before, there seemed to be a substantial tendency for city agencies to contact other city agencies. For a city respondent, odds that a potential city alter was named were about 100 times greater than the odds a potential county alter was named. The distance effect was quite large also. Suppose we compare two otherwise equivalent potential alters who differed in their distance from the responding agency, with the first the 10th closest (logged rank of distance =

2.303) and the second the 100th closest (logged rank of distance = 4.605). Then odds of being named in Question 1 were about 7 times greater (exp[1.968]) for the closer potential alter. Finally, the signs of the coefficients differed for the logged population ratio and squared logged population ratio variables. The pattern of signs indicates that an alter was more likely to be named as the ratio increased, but that the impact of additional size decreased until a point at which greater size meant lower odds of being named. From the coefficients, this point was at logged population ratio = 3.789, or population ratio roughly 44. (Such a point was achievable in the data; there would, for instance, be many agencies for whom New York City's population was 44 times greater than their own.) This suggests that while greater size generally made a potential alter more attractive as a contact, at some point the alter's size was so great that the agency may have been perceived as too different to be of much help.

4. Network Ties and Innovation

We now turn to the relationship between network ties and innovation. Our strategy was to study the adoption of a practice (or change in the presence or absence of the practice) by responding agencies, and investigate whether the presence or absence of the practice in the responding agencies' named network contacts influenced the probability of adoption. (In cases of multiple named alters, we used the first listed.) For short, we refer to such influence as "network effects", although more precisely they represent a difference in innovation between those agencies whose alters do and those agencies whose alters do not exhibit some characteristic. We studied several areas, with data from LEMAS: (i) the presence of a community policing plan, (ii) geographic assignment of detectives, (iii) encouragement of SARA (Scanning, Analysis, Response, and Assessment) problem-solving as an agency practice, and use of computers for (iv) crime mapping and (v) resource allocation.[10] The first three areas deal with aspects of community policing, and are thus likely to be of public interest. The last two are likely of technical interest to police professionals, not the general public. Along with representing different sorts of innovations, these areas also appeared promising for analysis because there were plenty of agencies with and without the characteristic in the different administrations of LEMAS. Of course focusing on different areas could perhaps lead to different results (as noted by Weiss, 1997b), but if there are broad regularities in the impact of network ties on police innovation adoption, they should be apparent in these areas.

We used LEMAS responses from 1997 and 2000, as the 1997 date was reasonably close to the administration of the network survey. We conducted analyses using both adoption of a practice (looking at those agencies that reported not having the practice in place in 1997, and seeing whether they had it in place in 2000) and change in the presence or absence of a practice (for all agencies, seeing if the 2000 response regarding the practice differed from that in 1997). Throughout this section we focus on only the 225 city or county respondents that named a city or county agency for Question 1 (with further restrictions necessary for particular analyses).

4.1 Community Policing

For our analyses, we combined the responses "no", and "yes, not formally written", so that we studied the distinction between agencies with a formal community policing plan and those without a formal plan. Table 4.1.1 summarizes responding agencies' community policing plans in 1997 and 2000.

Table 4.1.1 Respondents' Community Policing Plans, 1997 and 2000

	2000		
1997	Formal	No / Informal	Missing
Formal	95	44	2
No / Informal	3	45	2
Missing	2	1	0

For many agencies there was no change between 1997 and 2000, but a surprisingly large number did change, including many abandoning their formal plan. (Abandonment could be due to pervasive integration of community policing principles into an agency's activities, but it seems there would still be symbolic value in a formal plan in that case.)

4.1.1 Adoption of Community Policing

To study adoption of community policing, we examined the responding agencies that reported no (or an informal) community policing plan in 1997. Table 4.1.1 indicates 79 such agencies with non-missing information for 2000, with 34 adopting in 2000. While agency characteristics such as size and type likely influence adoption, our primary interest was in network effects. There were a variety of possibilities for representing the network effects. We used the following in separate analyses: the most frequently contacted (Question 1) agency's response to the LEMAS community policing question in 1997, 1999, and 2000, and the most frequently contacted regarding community policing (Question 10D) agency's response to the LEMAS community policing question in 1997, 1999, and 2000. When multiple agencies were named by the respondent for Question 1 or Question 10D, the first named was used.

Table 4.1.1.1 presents logit models for the dependent variable adoption (1 = adopted by 2000, 0 = did not adopt). Each column represents a different specification of the network effect; each uses the presence of a formal community policing plan in the most frequently contacted (Question 1) agency, but for different LEMAS years.

Table 4.1.1.1 Models for Adoption of a Formal Community Policing Plan in 2000, for Respondents Without a Plan in 1997, Using Most Frequent General Contact

	Year of Most Frequently Contacted Agency's Data		
	1997	1999	2000
Intercept	-3.896	-2.885	-3.699
Type City	-0.072 (0.945)	-0.099 (0.955)	-0.093 (0.954)
Log Population	0.316 (0.315)	0.254 (0.311)	0.276 (0.308)
Presence of CP Plan, Network Alter	-0.221 (0.526)	-0.293 (0.530)	0.279 (0.491)
N	72	74	74

In none of the models was the network effect statistically significant; in fact, none of the factors had statistically significant effects in any of the models. There is little evidence here for systematic influences, network or otherwise, on the adoption of community policing plans.

The analyses in Table 4.1.1.1 used the most frequent general contact (Question 1). Perhaps a network effect is detectable if the alter named in the specific domain of community policing (Question 10D) were used instead. Table 4.1.1.2 repeats the analyses with the alter named in Question 10D; the arrangement of the Table is otherwise the same.

Table 4.1.1.2 Models for Adoption of a Formal Community Policing Plan in 2000, for Respondents Without a Plan in 1997, Using Most Frequent Community Policing Contact

	Year of Most Frequently Contacted Agency's Data		
	1997	1999	2000
Intercept	-3.619	-3.137	-3.339
Type City	-0.193 (1.064)	-0.157 (0.924)	-0.284 (0.930)
Log Population	0.226 (0.313)	0.240 (0.304)	0.252 (0.305)
Presence of CP Plan, Network Alter	0.882 (0.667)	0.054 (0.438)	0.419 (0.518)
N	67	69	69

Again none of the variables had statistically significant effects in any of the models. The network effect begins to approach significance in the model using the alter's 1997 data, and the sign of the estimated coefficient was sensible (greater chance of the responding agency's adopting a formal plan when the alter had one in 1997). But it was not significant at conventional levels.

4.1.2 <u>Change in the Presence or Absence of Community Policing Plan</u>

Studying adoption may not be the best approach. An alternative is to study change rather than adoption. Then all responding agencies (with complete data) are examined, rather than just those which did not have a plan in 1997. The dependent variable would indicate whether or not the agency's status with respect to the community policing plan changed, without specifying whether the change was from having a plan to not having one or vice versa. The network variable needs to be constructed somewhat differently with this sort of dependent variable. We examined three possibilities (in separate analyses). The first was whether the responding agency and its named alter differed in their community policing plan status in 1997. The idea with this specification was that a difference might "push" the responding agency toward change. A slightly different formulation would be whether the named alter's status in 2000 differed from the responding agency's status in 1997; this specification imagines that the contact's status in the later period might "pull" the responding agency toward change. Finally, we considered change in the alter's status between 1997 and 2000, thinking that change on the alter's part may make change on the responding agency's part more likely. This specification does not seem as logically solid as the first two, but we included it for comparison. Table 4.1.2.1 reports logit models for change in the responding agency's status from 1997 to 2000.

Table 4.1.2.1 Models for Change in Community Policing Plan Status from 1997 to 2000, Using Most Frequent General Contact

	Specification of Network Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	1.328	1.551	1.378
Type City	-0.360 (0.593)	-0.374 (0.593)	-0.344 (0.595)
Log Population	-0.142 (0.183)	-0.151 (0.181)	-0.142 (0.181)
Network Variable	0.057 (0.298)	-0.180 (0.300)	-0.116 (0.310)
N	206	206	206

As with the earlier adoption formulation, none of the factors in the models appeared to influence the probability of change. The situation seemed to be the same as with adoption: there was little evidence for systematic influences on change in agency's community policing status. Again it may be more appropriate to use the alter named specifically for community policing (Question 10D). Table 4.1.2.2 reports analyses based on the alter (first listed, if multiple present) named in Question 10D. As before, these analyses showed no significant influences on change in community policing status.

Table 4.1.2.2 Models for Change in Community Policing Plan Status from 1997 to 2000, Using Most Frequent Community Policing Contact

	Specification of Network Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	0.082	0.510	-0.821
Type City	-0.032 (0.608)	-0.005 (0.607)	0.051 (0.608)
Log Population	-0.084 (0.187)	-0.116 (0.185)	0.125 (0.184)
Network Variable	0.436 (0.316)	0.292 (0.317)	0.145 (0.328)
N	194	194	194

4.2 Geographic Assignment of Detectives

Next we turn to influences on the practice of geographic assignment of detectives. Similar to the analyses of community policing, we examined both adoption of and change in geographic assignment of detectives as dependent variables, and used several different specifications of the network effect.

4.2.1 Adoption of Geographic Assignment of Detectives

For analyses of adoption, we focused only on agencies which reported that they did not employ geographic assignment of detectives in 1997. Table 4.2.1.1 gives results from analyses of adoption. We used the most frequent community policing contact (Question 10D).

Table 4.2.1.1 Models for Adoption of Geographic Assignment of Detectives in 2000, for Respondents Not Doing So in 1997, Using Most Frequent Community Policing Contact

	Year of Most Frequently Contacted Agency's Data		
	1997	1999	2000
Intercept	-16.578	-15.917	-16.009
Type City	0.160 (1.146)	-0.135 (1.097)	-0.286 (1.093)
Log Population	1.325 (0.365)**	1.299 (0.363)**	1.303 (0.360)**
Presence of Geog. Asgn., Network Alter	0.687 (0.486)	0.521 (0.533)	0.761 (0.551)
N	108	108	108

Population had a statistically significant, positive effect on the probability of adoption of geographic assignment of detectives. Larger agencies were more likely to adopt this practice. If we use b = 1.3 (as a crude average across models), a 10% increase in population would increase odds of adoption by about 13%. The network effect approached statistical significance in two of the models, but did not reach it.

4.2.2 Change in Geographic Assignment of Detectives

Table 4.2.2.1 reports on analyses of change in an agency's use of geographic assignment of detectives, with the several formulations of the network effect. These analyses used the contact named for community policing (Question 10D).

Table 4.2.2.1 Models for Change in Geographic Assignment of Detectives from 1997 to 2000, Using Most Frequent Community Policing Contact

	Specification of Network Alter Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	-5.803	-4.541	-3.642
Type City	-0.040 (0.588)	-0.145 (0.575)	-0.191 (0.574)
Log Population	0.374 (0.187)*	0.293 (0.181)	0.249 (0.178)
Network Alter Variable	1.115 (0.335)**	0.646 (0.324)*	0.054 (0.358)
N	194	194	194

The population effect was significant in the first model (although not as large as in the prior analysis of adoption) and borderline significant in the second. The network alter effect was significant when formulated in terms of difference between the alter and respondent, but not when formulated in terms of change in the alter's status. The two formulations of the network effect suggested a push and pull of the alter's use (or disuse) of geographic assignment. In the first model, the odds of the responding agency changing its use of geographic assignment were estimated to be about 3 times greater when the community policing alter's use of geographic assignment in 1997 differed from the respondent's at that time than when it did not.

4.3 SARA

For encouragement of SARA-type problem-solving, we examined the alter (or first listed alter) named for Question 10E on problem-oriented policing. Otherwise the analyses followed the same framework as for geographic assignment of detectives.

4.3.1 Initiation of Encouragement of SARA Problem-Solving

Table 4.3.1.1 presents results from the analysis of those agencies that did not report encouragement of SARA in 1997, with the various formulations of the network effect.

Table 4.3.1.1 Models for Initiation of Encouragement of SARA in 2000, for Respondents Not Doing So in 1997, Using Most Frequent Problem-Oriented Policing Contact

	Year of Most Frequently Contacted Agency's Data		
	1997	1999	2000
Intercept	-7.162	-7.439	-7.586
Type City	1.731 (0.867)*	1.737 (0.864)*	2.014 (0.937)*
Log Population	0.461 (0.246)#	0.469 (0.247)#	0.526 (0.262)*
Presence of SARA Enc., Network Alter	0.116 (0.510)	0.346 (0.547)	-0.632 (0.660)
N	76	76	76

The pattern appeared the same across the different network variables: a significant difference between city and county agencies (with odds of initiation considerably higher for city agencies) and a significant population effect, but no significance of the network effect.

4.3.2 Change in Encouragement of SARA Problem-Solving

We also examined 1997 to 2000 change in reported encouragement of SARA-type problem-solving by responding agencies. Table 4.3.2.1 gives results for analyses with different specifications of the network effect (again based on Question 10E).

Table 4.3.2.1 Models for Change in Encouragement of SARA Problem-Solving from 1997 to 2000, Using Most Frequent Problem-Oriented Policing Contact

	Specification of Network Alter Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	-5.478	-5.250	-4.821
Type City	0.744 (0.595)	0.644 (0.585)	0.643 (0.587)
Log Population	0.296 (0.169)#	0.288 (0.167)#	0.274 (0.165)#
Network Alter Variable	1.070 (0.338)**	0.847 (0.331)*	0.531 (0.373)
N	183	183	183

Population had a (borderline) statistically significant effect across the different models, while the city/county difference did not reach statistical significance. The network variable had a significant impact under the first two specifications (based on the comparison of respondent's and alter's encouragement of SARA). The impact was not significant under the third specification (change in the alter's encouragement of SARA). For the first two models, the size of the network effect seemed fairly substantial. From the first estimated b, a difference between respondent and alter on SARA in 1997 lead to almost three times greater odds of the respondent changing regarding SARA than if the respondent and alter did not differ on SARA. From the second estimated b, a difference on SARA between the respondent in 1997 and the alter in 2000 was associated with 2.3 times greater odds of the respondent changing than if there were no difference.

4.4 Use of Computers for Resource Allocation

For analysis of adoption of, or change in, the use of computers for resource allocation, none of the specific domains of Question 10 seemed exactly relevant. Therefore we used alters named in Question 1 in the network variables.

4.4.1 Adoption of Computer Use for Resource Allocation

Table 4.4.1.1 reports results of analyses of adoption of computer use for resource allocation (among those agencies reporting that they did not use computers for this purpose in 1997). Again the various specifications of the network effect were based on Question 1.

Table 4.4.1.1 Models for Adoption of Computer Use for Resource Allocation in 2000, for Respondents Not Doing So in 1997, Using Most Frequent General Contact

	Year of Most Frequently Contacted Agency's Data	
	1997	2000
Intercept	-10.414	-10.310
Type City	0.472 (1.127)	0.466 (1.127)
Log Population	0.753 (0.337)*	0.752 (0.337)*
Presence of Comp. Use for Res. Alloc., Network Alter	0.283 (0.555)	0.197 (0.499)
N	93	93

The statistically significant population effect was in the expected direction: larger agencies were more likely to adopt computer use for resource allocation. (The estimated population effect meant that for 10% additional population, an agency's odds of adopting computer use for resource allocation increased by slightly more than 7%.) However there did not seem to be a network influence on adoption, as the observed network effects did not even approach statistical significance.

4.4.2 Change in the Use of Computers for Resource Allocation

As with the other areas of innovation, we repeated the analyses with change between 1997 and 2000 in the responding agency's computer use as the dependent variable. Table 4.4.2.1 gives these results for the different formulations of the network effect (all based on Question 1).

Table 4.4.2.1 Models for Change in Use of Computers for Resource Allocation from 1997 to 2000, Using Most Frequent General Contact

	Specification of Network Alter Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	-2.620	-2.612	-2.304
Type City	0.217 (0.588)	0.209 (0.587)	0.199 (0.588)
Log Population	0.158 (0.176)	0.158 (0.180)	0.139 (0.174)
Network Alter Variable	0.083 (0.295)	0.064 (0.304)	-0.076 (0.298)
N	207	207	207

None of the posited influences on change in computer use for resource allocation were statistically significant in any of the models. The network variable in particular did not come close to achieving significance under any of the three specifications.

4.5 Use of Computers for Crime Mapping

The final innovation area that we examined was the use of computers for crime mapping. As with computer use for resource allocation, none of the particular domains in Question 10 were directly relevant, so we used the general network alter named (or first named) in Question 1.

4.5.1 Adoption of Computer Use for Crime Mapping

Table 4.5.1.1 presents results from analyses of the adoption of computer use for crime mapping, among those responding agencies reporting no such use in 1997. Again the different models refer to different specifications of the network effect.

Table 4.5.1.1 Models for Adoption of Computer Use for Crime Mapping in 2000, for Respondents Not Doing So in 1997, Using Most Frequent General Contact

	Year of Most Frequently Contacted Agency's Data		
	1997	1999	2000
Intercept	-16.238	-14.539	-15.300
Type City	3.346 (1.857)#	2.975 (1.736)#	3.250 (1.692)#
Log Population	1.050 (0.545)#	0.957 (0.511)#	0.978 (0.518)#
Presence of Comp. Use for Cr. Map., Network Alter	1.543 (0.670)*	1.078 (0.760)	1.416 (0.741)#
N	67	67	67

Results indicated a (borderline) statistically significant city / county difference that was also quite large in real terms: the estimated odds of adoption of computer use for crime mapping by city agencies were roughly 20 times those of adoption by county agencies. This estimate may, however, be vulnerable to the small number of county agencies left in this analysis (note the large standard error), so the precise estimate may not be as trustworthy as some. The population effect also was borderline statistically significant, and suggested that a 10% greater population increased odds of adoption by about 10%. The network effect was statistically significant (or borderline significant) in two of the models, those using the 1997 and 2000 alter information. An estimated b of 1.5 translates into somewhat more than 4 times greater odds of adoption for those agencies whose alter had computer use for crime mapping in place.

4.5.2 Change in Computer Use for Crime Mapping

We next analyzed change in the use of computers for crime mapping. Table 4.5.2.1 reports results for the various specifications of the network effect (based on Question 1).

Table 4.5.2.1 Models for Change in Use of Computers for Crime Mapping from 1997 to 2000, Using Most Frequent General Contact

	Specification of Network Alter Variable		
	Different from Respondent in 1997	Alter in 2000 Differs from Respondent in 1997	Change in Alter's Status from 1997 to 2000
Intercept	2.227	1.464	7.224
Type City	-0.405 (0.744)	-0.259 (0.749)	-0.680 (0.686)
Log Population	-0.313 (0.238)	-0.258 (0.239)	-0.640 (0.224)**
Network Alter Variable	1.890 (0.358)**	1.968 (0.362)**	0.012 (0.441)
N	207	207	207

In the first two network specifications, the network effect was statistically significant (and rather large: odds of change were estimated to be almost 7 times greater for respondents whose alter differed from them on crime mapping than for those whose alter did not). The third version of the network variable did not have a statistically significant impact. Perhaps that is expected, given the various results above, but note the negative (and significant) estimated effect of population. Estimates for the non-network coefficients in this model were virtually identical to those obtained when the model included only type city and log population, and the estimate for the network coefficient was fairly similar to that obtained when the model included the network effect only.[11] Given the results for adoption in Table 4.5.1.1, the negative effect of population on change may result from a large negative effect of population on dropping computer use for crime mapping. This may be plausible, but in light of the results for the models with fewer parameters, the explanation that the apparent effect of population disappeared when controlling for a properly specified network variable is likely preferable.

5. Discussion

5.1 Network Results

The results in section 3 leave no doubt that are systematic regularities in agencies' choices of network contacts. It would be excessive to review all those results again, but we will comment on some main findings. The models for the general characteristics of the named contact (section 3.1) show that features of the responding agency significantly influenced the choice of network alter. Similarly, the analysis of which particular agency was chosen (section 3.4) shows that agency characteristics and geographical distance were important factors in this choice. Many of these findings seem consistent with past work on organizational networks in general; while geographical considerations may be more pressing for a police department (the duties of which are explicitly restricted to a given city or county) than for other sorts of organizations, geographical proximity is expected to be important in networks of many types.

Throughout these analyses it has been suggested that agencies tended to choose larger agencies as contacts (with indications of size-related asymmetry in the contact network; section 3.2), and that there was a tendency to choose agencies of the same type, although in some analyses this tendency appeared more pronounced for city than for county agencies (note analyses in section 3.3.2). There is evidence, then, for both of the potential organizing principles, "exchange" and "homophily", that were discussed in the literature review. A tendency to contact larger agencies suggests that such agencies are perceived as better sources of information, with access to facts and resources that the (smaller) responding agency would not have. That seems to suggest "exchange" as a primary motivation in network choice. Of course there are other potential explanations for this phenomenon—there may be automatic legitimacy for an agency staffer who reports having consulted with a large, well-known department, while information whose source is a smaller agency may be greeted with skepticism by others in the department.[12] But an exchange perspective is at least consistent with this observation. Likewise results on agency type suggest a tendency toward homophilous choices on various dimensions. Again, though, population had an important influence, as results showed that agency size influenced the probability of making an in-state choice (less likely for larger agencies, or when the agency is the largest in its state; section 3.1.1) and the probability of choosing an agency of the same type (more likely for larger agencies; section 3.1.2).[13]

It is incorrect, however, to draw the conclusion that agency's network alters were exclusively the result of mechanical choices (conscious or not) based on the factors such as size, type, state boundaries and geographical distance. Though methodologically crude, our identification of "relative experts" in the various domains (section 3.3.3) still indicates that agencies, or more accurately, planners within those agencies, perceived different agencies as more or less valuable sources of information. This perception remained even after accounting for structural influences on choice of alters (as embodied in the responses to the general Question 1). That this perception appeared stronger in domains that are likely more interesting to the general public suggests that perhaps pressures on departments to get things right are stronger in these areas. Part of convincing civilian leadership that the department is getting things right may be showing that consultations are with expert departments (echoing the legitimacy argument above for agency size). Our analyses of Question 10 benefit in this respect from the comparison to choices made on Question 1. Were there available direct measures of perceived general expertise, it seems likely that they would have influenced general network choice (Question 1) even beyond the structural factors we considered.

5.2 Innovation Results

Results from the innovation analyses were somewhat mixed, so it is worthwhile to review the main patterns apparent in the tables. First, estimated network effects were almost always in the expected direction, except for the third specification in the change analyses, although the effects often did not reach statistical significance (across all the tables and all specifications of the network effect, eight statistically significant network effects were observed). The large majority (six) of these were in the analyses of change (adoption or discontinuance), with only two in the analyses of adoption alone. In the analyses of change, the network effect based on change in the alter status between 1997 and 2000 was not statistically significant in any of the analyses, while the network effects based on difference between respondent and alter were significant in half of the analyses. The presence of statistically significant network effects did not seem to track with the supposed distinction between types of innovation. The network effects were not statistically significant for the high profile community policing innovation, but neither were they for the decidedly low profile computer use for resource allocation. Significant network effects were seen for SARA and geographic assignment detectives, and they were also seen for computer use for crime mapping.

Of course it can be dangerous to informally summarize a large number of analyses. Even there really were no network effect, some statistically significant results would likely appear simply due to chance. And the results for different dependent variables, much less different analyses of the same dependent variable, cannot properly be viewed as independent replications.

Still, from these results it appears quite plausible that there are real network effects. That the "alter change" specification yields no significant effects (and in many cases counter-intuitive negative estimates) seems reasonable. The forces of "push" and "pull" embodied in the formulations based on difference between alter in 1997 and 2000 and respondent in 1997 are easy to make sense of conceptually. But unless the alter's change itself inspires respondents to change, it is harder to imagine a systematic effect of alter's change. There is no intuitive reason why consistent network effects should be more apparent in analyses of change than in analyses of adoption, although in some cases the larger sample sizes for the change analyses may be an explanation.

While the results thus offer some evidence for social learning as an innovation driver (National Research Council 2004), detection of network effects was not completely consistent. We can speculate on possible reasons for this, noting of course that the data at hand do not allow us to test our speculation. Of course it is possible that network effects are simply not too substantial, and were thus difficult to detect in the modestly sized samples here. Another possibility is that the timing of network influence and subsequent response did not correspond perfectly to the timeline used here, with network data collected in 1996 and agency behavior observed in 1997 and 2000. The data gave little choice as to the timeline, but, should it be suboptimal, we would expect a dampening of any observed network effects. Also, the network measurements themselves may be problematic. It is possible that the relation being measured here was not completely appropriate. We have already mentioned the large number of possible relations between departments, and the likelihood that different types of ties are important for different aspects of agency management and operations. Ties between planners at different agencies may not be the best way to capture network influences on many sorts of innovation adoption (or change in practices). Another potential source of difficulty is the use of the first listed agency (in the many cases in which more than one was named for a question). Of course the survey instructions were to name just one, so we assumed that if the responder disregarded these instructions they named the most important network contact first. This is not necessarily correct; in a number—not too great, but non-trivial—of cases it appeared that multiple agencies were listed alphabetically. To the extent that the network contact most likely to influence behavior of the responding agency was listed later than first, we would expect truncation of observed network influences.

Finally, Weiss (1997) and National Research Council (2004) raise questions of the fundamental quality of agency responses to surveys such as LEMAS and, by implication, the network survey. Responses (on questions of fact, not attitude) can differ substantially depending on which individual staff member was responsible for completing the survey. Accurate responses depend on the knowledge possessed by the staffer and their willingness to seek out others within the agency who would have accurate information. Unfortunately it seems likely that accurate completion of the survey may have low priority among all the tasks facing the staffer, who thus may not have great incentive to spend enough time running down information to assure accurate responses. (Substantial non-response to the network items was also suggestive of this possibility.) These basic data quality issues would affect both the network and LEMAS data. While it is not obvious how errors introduced this way would affect the estimated impact of network ties on innovation, we cannot exclude the possibility that they have. Our speculation on these matters is just that, so nothing we have said here is meant to discount the possibility that network effects are simply not always very strong. But these issues may, along with relatively small sample sizes, make detection of network effects rather challenging.

5.3 Policy Implications

In general it is difficult to draw direct policy implications from innovation research. National Research Council (2004) concluded from their review of the existing police innovation literature that inconsistency of findings "limits the ability of the committee to draw comprehensive conclusions that are sure to be useful to policy makers (p. 99)" and that ultimately "little is known about the innovation process or how it can be facilitated (p. 107)." Here we are not trying to provide an overview of the entire innovation process, nor evaluate the efficacy of particular innovations, so for the most part implications we draw must be limited to the network element of innovation. To the extent that it is possible to say something about the innovation process, the results reinforce the idea that different kinds of innovations must be viewed as distinct, with potentially distinct influences, rather than as simply examples of a generic innovation process. That is not to say that there are no regularities that apply across types of innovation; in fact, we saw evidence of that and are, if anything, predisposed to look for regularities first and differences second. But the results do offer some caution against simplistically assuming that innovation in one area of policing will work the same way as in any other area. Programs to encourage innovation must recognize possible differences.

If we assume that there are indeed network effects, our focus is drawn to the formation of ties that precede influence on innovation. The results indicate that structural features like size, type, and geographical location had much to do with the presence and absence of network ties.

However the results for expertise suggest that agencies did make some effort to find the best sources of information on a particular topic, even if those sources would not necessarily be frequent general contacts. To make the search for expert help most effective, the policing research community needs to devote substantial effort to systematically identifying and publicizing agencies with expertise in certain aspects of policing. As is, Weiss (2001; cited in National Research Council [2004]) indicates that agencies selected to house demonstration projects of various sorts become de facto experts and are targets of requests for advice, but identified expertise could go beyond the presence of formalized demonstration projects. The practical difficulty, of course, is that genuine identification of expertise would require significant resources, as identification would have to go beyond responses to LEMAS (or similar surveys) to include site visits and direct observation. But if agencies are attempting to contact others based on perceived expertise, it would be desirable to replace hazy perceptions with empirically justified identification of expert departments.

Efforts such as those suggested by Redmond and Baveja (2002) would go a step further and, in effect, induce network ties between particular agencies. The results here provide some justification for such strategies, as the evidence mainly supported the idea of network effects on innovation. But the findings for the network ties also indicate that the “natural” process of tie formation is heavily shaped by the structural factors of size, type, and geography. An attempt to create contacts between particular agencies can thus adopt one of two main strategies. One approach would be to identify pairs of agencies that “should” be in contact based on the main patterns identified with the structural factors. Or the strategy could be to “go against” the patterns identified in the mass of network data, and try to create contacts between agencies that would be otherwise unlikely to be in communication. The choice parallels the distinction between the homophily and exchange motivations for network ties, although the issue of size is, as we have seen, complicated by the tendency in the data for agencies to seek contact with larger departments. The first strategy is more straightforward than the second, as the second would confront the difficulty of examining a very large number of potential alters. Also, the second only makes sense in conjunction with some identification of expertise as discussed above, as there is no reason to create a tie that will not transmit important information.

Aside from this practical difficulty, though, a possible argument for the second is that agencies are likely more aware of potential alters that are similar in various characteristics or geographically nearby. A choice not to initiate contact with such an agency may have resulted from prior contacts that were seen as not rich in information, or from observations that convinced the agency that the potential alter would not be useful. The second approach, on the other hand, would deal with potential alters that the agency may not have considered at all, due to relative size, distance, or differences in type, and thus seems to offer a potentially greater benefit. Of course the data in our study are not sufficient to determine rather structurally “anomalous” or structurally “expected” ties differ in their impact on innovation, so the choice of either approach would still have a speculative element.

The previous point is one of our reasons for echoing National Research Council’s (2004) call for further research on innovation. The data at hand offer tantalizing glimpses into the pattern of network ties and the impact of this pattern on innovation. But throughout we have commented on various ways in which the existing data do not allow us to satisfactorily address various interesting research questions. Of course this is by no means the fault of those who designed the original instruments and collected the data—as in all secondary data analysis, we come to a data set that was optimized, in the design and data collection stage, for the analysis intended then, not what we have attempted here. Still, to make policy recommendations with a reasonable degree of confidence, we will need to have data that are more closely adapted to the sort of research pursued in this study.

Finally, the network data are now rather old, and much has changed in policing since their collection. Perhaps the most important change for questions involving information has been the fantastic growth in online resources and universal access to them. Such resources existed at the time of the network data collection, and were cited by some respondents, but they are of a far greater importance in information gathering today. It is unclear to what extent this would impact the relationship between informal communication ties and innovation, and indeed how these changes would affect the structure of the communication ties themselves. This is another reason for the policing research community to support new efforts to gather network data.

References

Agresti, A. 2002. *Categorical Data Analysis*. Hoboken, NJ: Wiley.

Banaszak-Holl, J., Allen, S., Mor, V., & Schott, T. 1998. Organizational characteristics associated with agency position in community care networks. *Journal of Health and Social Behavior* 39:368-385.

Chamard, S. E. 2003. *Innovation-Diffusion Networks and the Adoption and Discontinuance of Computerized Crime Mapping by Municipal Police Departments in New Jersey*. PhD dissertation, Rutgers University.

Coleman, J. S., Katz, E., & Menzel, H. 1966. *Medical Innovation: A Diffusion Study*. New York: Bobbs Merrill.

Galaskiewicz, J. & Burt, R. S. 1991. Interorganization contagion in corporate philanthropy. *Administrative Science Quarterly* 36:88-105.

Galaskiewicz, J. & Wasserman, S. 1989. Mimetic processes within an interorganizational field: An empirical test. *Administrative Science Quarterly* 34:454-479.

Gulati, R. & Gargiulo, M. 1999. Where do interorganizational networks come from? *American Journal of Sociology* 104:1439-1493.

Heanue, K. & Jacobson, D. 2001. Organizational proximity and institutional learning: The evolution of a spatially dispersed network in the Irish furniture industry. *International Studies of Management and Organization* 31:56-72.

Johnson, J. D. 1992. Technological and spatial factors related to organizational communication structure. *Journal of Managerial Issues* 4:190-209.

Kearns, K.P. 1989. Communication networks among municipal administrators. *Knowledge: Creation, Diffusion, Utilization* 10:260-279.

Kearns, K. P. 1992. Innovations in local government: A sociocognitive network approach. *Knowledge and Policy* 5:45-67.

Kelley, M. R. & Brooks, H. 1991. External learning opportunities and the diffusion of process innovations to small firms: The case of programmable automation. *Technological Forecasting and Social Change* 39:103-125.

King, W. R. 2000. Measuring police innovation: Issues and measurement. *Policing* 23:303-317.

Lincoln, J. R. & McBride, K. 1985. Homophily, and dependence: Organizational attributes and asymmetric ties in human service networks. *Social Science Research* 14:1-30.

Manning, P. K. 1992a. Technological dramas and the police: Statement and counterstatement in organizational analysis. *Criminology* 30:327-346.

Manning, P. K. 1992b. Informational technologies and the police. Pp. 349-398 in *Modern Policing*, M. Tonry & N. Morris, Eds. Chicago: University of Chicago Press.

Marsden, P. V. 1981. Models and methods for characterizing the structural parameters of groups. *Social Networks* 3:1-27.

Mizruchi, M. S. 1993. Cohesion, equivalence, and similarity of behavior: A theoretical and empirical assessment. *Social Networks* 15:275-307.

Monkkonen, E. 1981. *Police in Urban America: 1860-1920.* Cambridge: Cambridge University Press.

Moore, M. H., Sparrow, M., & Spelman, W. 1997. Innovations in policing: From production lines to job shops. Pp. 274-298 in *Innovation in American Government*, A. A. Altshuler & R. D. Behn, Eds. Washington, DC: Brookings Institution Press.

National Research Council. 2004. *Fairness and Effectiveness in Policing: The Evidence.* Committee to Review Research on Police Policy and Procedures. W. Skogan & K. Frydl, Eds. Washington: National Academies Press.

Oliver, A. & Ebers, M. 1998. Networking network studies: An analysis of conceptual configurations in the study of inter-organizational relationships. *Organization Studies* 19: 549-583.

Powell, W. W, Koput, K. W, & Smith-Doerr, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly* 41:116-145.

Raftery, A. E. 1995. Bayesian model selection in social research (with discussion). *Sociological Methodology* 25:111-195.

Redmond, M. & Baveja, A. 2002. A data-driven software tool for enabling cooperative information sharing among police departments. *European Journal of Operational Research* 141:660-678.

Roberts, J. M., Jr. 2000. Correspondence analysis of two mode network data. *Social Networks* 22:65-72.

Rogers, E. M. 1962. *Diffusion of Innovations*. New York: Free Press.

Rothwell, R. 1991. External networking and innovation in small and medium-sized manufacturing firms in Europe. *Technovation* 11: 93-112.

Sandell, R. 2002. Social networks and organizational similarity: an analysis of similarities in chairperson remuneration among Sweden's publicly traded firms. *Scandinavian Journal of Management* 18:47-64.

Skolnick, J. H. & Bayley, D. H. 1986. *The New Blue Line: Police Innovation in Six American Cities*. New York: Free Press.

Sobel, M. E., Becker, M. P., & Minick, S. M. 1998. Origins, destinations, and association in occupational mobility. *American Journal of Sociology* 104:687-721.

Strang, D. & Soule, S. A. 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology* 24:265-290.

Wasserman, S. & Faust, K. 1994. *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.

Weisburd, D., Uchida, C., & Green, L. (Eds.) 1993. *Police Innovation and Control of the Police: Problems of Law, Order, and Community*. New York: Springer-Verlag.

Weiss, A. 1997a. *Communication of Innovation in Policing in the United States, 1996* [computer file] ICPSR version. Bloomington, IN: Indiana University [producer]. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 1999.

Weiss, A. 1997b. The communication of innovation in American policing. *Policing* 20:292-310.

Weiss, A. 1998a. *Enhancing the Dissemination of Innovation in Community Policing: The Role of Information Sharing; Final report*. National Institute of Justice, NCJ 171553.

Weiss, A. 1998b. Informal information sharing among police agencies. *National Institute of Justice Research Preview*. December, FS 000233.

Weiss, A. 2001. Police innovation and communication networks. Paper prepared for National Research Council Committee to Review Research on Police Policy and Procedures. (Cited in National Research Council [2004]).

Weller, S. C. & Romney, A. K. 1990. *Metric Scaling*. Beverly Hills, CA: Sage.

Wejnert, B. 2002. Integrating models of diffusion of innovations: A conceptual framework. *Annual Review of Sociology* 28:297-326.

Wholey, D. R. & Huonker, J. W. 1993. Effects of generalism and niche overlap on network linkages among youth service agencies. *Academy of Management Journal* 36: 349-371.

Williamson, I. O. & Cable, D. M. 2003. Organizational hiring patterns, interfirm network ties, and interorganizational imitation. *Academy of Management Journal* 46:349-358.

Woodard, K. L. & Doreian, P. 1994. Utilizing and understanding community service provision networks: A report of three case studies having 583 participants. *Journal of Social Service Research* 18:1-41.

Notes

1. For our analyses, we did not use all 416 agencies. Some could not be found in all the years of LEMAS we used, and two had data anomalies that made us distrust their records. The ID numbers of the agencies we did not use were 1128, 1130, 1140, 1252, 1254, 1372, 1392, 1484, 1498, 1569. This left 406 agencies; we also did not use the one tribal agency, leaving a maximum of 405 agencies in any of our analyses. As discussed below, non-response meant that generally fewer appeared in any one analysis.

2. This issue was indirectly recognized in Weiss (1998a). It was reported there that data on the contacts of the 220 city or county agencies described above were entered into UCINET, a computer program for structural analysis of social networks. However the only analysis reported was on the number of times various agencies were mentioned, not any structural features of the entire network.

3. We also conducted an analysis with an indicator for states in which the usual duties of the sheriff often do not include patrol responsibilities for a geographic area. (We flagged Connecticut, Delaware, Massachusetts, New Hampshire, New Jersey, Pennsylvania, and Rhode Island with this variable.) We investigated this because the different responsibilities of the sheriff in these states could account for some of the tendency toward same type choice by city agencies. (In these states, there may be particularly little perceived similarity between city and county agencies, and thus an especially strong tendency toward same type choices by responding city agencies; note, however, that a city agency in such a state could still make a different type

choice by contacting a state or national agency.) Addition of this variable to the models in the table did not significantly change model fit or substantially change parameter estimates.

4. Again flagging states with different sheriff duties did not have any appreciable impact.

5. In these data, equal populations only occurred when the same agency was named for both questions. The table indicates this occurred 37 times, not 42 as given earlier. The earlier figure was based on first listed agencies, while the current figure is based on maximum population. The first listed agency may have been the same for both questions yet not the largest listed population for either question if there were multiple agencies named.

6. This sum differed substantially across pairs of domains, because responding agencies named different numbers of alters in different domains.

7. This is not the classic frequency table for which correspondence analysis is usually used. But correspondence analysis also functions well as a general multidimensional scaling technique, and this is effectively a table of proximities.

8. We decided it would not be appropriate to include responses to the parts of Question 10. This would have the advantage of giving more cases with “yes” values on the dependent variable, but it seemed likely that different processes are involved with responses to the various parts of Question 10 than with responses to Question 1. So we did not mix them in the analysis.

9. Raftery (1995) gives many details on BIC. One practical interpretation of BIC is that the benefit (in -2 x log-likelihood) of using additional degrees of freedom must be at least {log N x (additional degrees of freedom used)} to represent a genuine improvement in fit. With N sufficiently large, this will be a more demanding standard than that implied by the usual comparison to the chi-square table for improvement at the 0.05 level.

10. In 1997 LEMAS, variable numbers were 472, 480, 481, 233, and 241, respectively. For 2000 LEMAS, variable numbers were 133, 143, 142, 208, and 218, respectively.

11. With only type city and log population included, estimates were (including the intercept) 7.233, -0.681, and -0.641, respectively; with only the (third) network variable, estimates were -0.968 and 0.169.

12. Such considerations may seem to call for an analysis of the survey data on reasons for contacting the agency named in Question 1. However we are suspicious of these ostensible reasons for a particular contact reported by the planner at the responding agency. They are as likely to be post-hoc explanations as they are to be genuine prior motivations for seeking information from a particular agency. So we do not report any analyses of those data.

13. Note also that agency characteristics were less consistently significant predictors of whether the alter was bigger or smaller than the responding agency (section 3.1.3).