

Social Constraints, Agency, Inter-organizational Tie Formation and Knowledge Diffusion

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ABSTRACT

Social capital is currently one of social structure's most prominent and debated manifestations. However, we have a limited understanding of how social ties as the basis of social capital form in the first place. From one perspective social capital is viewed as: "investment in social relations with expected returns in the marketplace" (Lin 2001, p. 19). A second perspective on social capital formation stresses contextual and environmental features beyond the control of individuals that may yield benefits. Both perspectives are based on premises implicating various motives and structural constraints pertaining to relationship formation including: exchange, power, and dependency; legitimacy seeking or preferential attachment based on status or prestige; homogeneity or homophily and related selection processes; propinquity; or cultural or institutional forces. These categories of mechanisms do not, however, specify a model of how social relationships as social capital are formed in the first place.

If social capital results from "investment strategies," it is important to determine what these strategies are. If social capital originates from structural factors beyond individual control it is important to clarify what mechanisms lead to tie formation within social structures.

The objective of this research is to specify mechanisms of social tie formation and reinforcement by peering inside the black-box of foci (Feld 1981) in which social ties are formed. We do so by focusing on the structural contexts within which individual (micro-level) "corporate actors" form social relationships for knowledge acquisition that results in macro-level knowledge sharing. A mixed-method analytical approach is employed to this end. Findings illustrate how the subtleties of social structure define the parameters within which social relationships are (strategically) formed.

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INTRODUCTION

Social capital is currently one of social structure's most prominent and debated manifestations (Bourdieu 1985; Portes and Sensenbrenner 1993; Portes 1998, 2000; Lin 2001), and its purview has been extended to various levels of social life from individuals to organizations to states and countries (Gulati 1999; Putnum 2000; Ingram, Robinson, and Busch 2005; Powell, White, Koput, and Smith 2005; Paxton 2007). Defining and describing what social capital entails and how it relates to (un)desirable outcomes has thus motivated substantial research (see Portes 1998; Mouw 2003, 2006 for reviews). However, we have a limited understanding of how social ties as the basis of social capital form in the first place (Sorenson and Stuart 2008). The objective of this research is to address this gap in the literature.

There are two primary views on the basis of social capital. From one perspective social capital is viewed as: "investment in social relations with expected returns in the marketplace" (Lin 2001, p. 19). Consistent with this view, Bourdieu (1985) argued that social capital arises from individual investment strategies of human and cultural capital in sociability. A second perspective on the origins of social capital stresses contextual and environmental features largely beyond the control of individuals. How social environments shape residents' life chances is an example (e.g., Wilson 1987; Mayer and Jencks 1989; Jencks and Mayer 1990; Sampson 2001; Sampson, Morenoff, and Gannon-Rowley 2002). The mechanisms linking macro social forces to individual outcomes can be blunt and blatant or sharp and subtle (e.g., Small 2009). However, a cornerstone of structuralist approaches is the idea that social context and the capital it affords are enabling or constraining above and beyond individual action (see generally Sampson 2008). Individuals begin life with varied levels of access to human capital, social networks, and a host of other productive or destructive conditions simply by virtue of whom their parents are and

where they live (Loury 1989, p. 272). These initial conditions, in turn, have a bearing on subsequent networking opportunities and outcomes, as well as human capital development (Coleman 1988).

Both of these overarching categories of social capital formation presuppose various motives for relationship formation and activation including: exchange and dependency (Homans 1958, 1961; Blau 1964; Yuchtman and Seashore 1967; Benson 1975; Cook 1975; Pfeffer and Salancik 1978; for a review see Cook and Whitmeyer 1992); legitimacy seeking or preferential attachment (e.g., Young and Larson 1965; Stuart 1998); or homogeneity or homophily and related social attraction and selection processes (McPherson, Smith-Lovin, and Cook 2001; see also Rauch 1997). Structural constraints and facilitators include propinquity (e.g., Powell, White, Koput, and Smith 2005; Sorenson and Stuart 2008) and cultural or institutional forces (Saxenian 1994; e.g., Almeida and Kogut 1999; Small 2009). Motives are, however, almost never observed; rather, they are extrapolated based on context. The motive compelling organizations to form relationships may presumably be resource dependencies (e.g., Pfeffer and Salancik 1978) and thus underlying economic logics of utility maximization generally defined. Similarly, structural features such as propinquity may lead to tie formation due to search cost minimization, homophily, or a higher likelihood of chance encounters. These presumed motives do not, however, reveal how social relationships as social capital are formed in the first place.

If social capital results from “investment strategies,” it is important to determine what these strategies are. This is not an easy task because the formation of a tie today is often the result of preexisting ties (see, e.g., Gulati and Gargiulo 1999). This endogeneity, as well as the opacity of network content (Burt 2008, p.953) and actors’ motivations result in considerable ambiguity about the origin of social ties as social capital. On the other hand, if social capital

originates from structural factors beyond individual control it is important to clarify what mechanisms lead to tie formation within social structures.

The objective of this research is to identify mechanisms of social tie formation and reinforcement by peering inside the black-box of foci (Feld 1981) in which knowledge sharing ties are formed (see Figure 1 below). We do so by focusing on the structural contexts within which individual (micro-level) “corporate actors”¹ form social relationships (link 3 in the figure) for knowledge acquisition that yield macro-level knowledge transmission (link 4 in the figure) (Alexander 1987; Blau 1987; Coleman 1987, 1994, 1998).

This focus on the action of corporate actors is important. As noted above, significant attention has been devoted to the patterns and consequences of the boundary spanning activities of macro social entities such as organizations. This research treats organizations as social actors in and of themselves that engage in this boundary spanning activity. This focus is sensible when describing the patterns of inter-organizational ties. However, it is not well-suited to reveal how organizations develop social capital and span boundaries in the first place. Observing that organizations in close proximity are more likely to have a joint venture agreement, for example, does not reveal how the agreement forms. Moreover, using individual-level mechanisms as explanations for patterns among macro-level social entities necessitates some consideration. This follows because organizations qua organizations do not run into each other at foci and decide to form joint ventures. Corporate actors make these links in concrete ways by and for themselves and on behalf of their organizations. And not all equally situated and endowed corporate actors

¹ We thus assume that organizations have institutionally defined and delegated rights, responsibilities, and incentives that enable their (micro level) agents to interact, engage, and establish formal and informal ties with other macro social entities (organizations) by interacting with other micro level corporate actors (Blau 1964; Coleman 1990, pp. 12-13; Ch. 16).

make these links in similar foci. Discerning differences and similarities across similarly situated corporate actors is thus important.

Insert Figure 1. about here

We employ a mixed-methods approach to do so. In the next section we describe the strategic research site—professional forensic DNA scientists employed in state crime laboratories. Survey data are then used to paint a picture of the social structure of knowledge sharing relationships and constraints among these labs across states. We employ these quantitative methods for descriptive rather than predictive purposes, so formal hypotheses are not proposed. Focus is then devoted to the qualitative evidence, which is particularly well suited to inform *how* knowledge sharing relationships form within foci, which is the novel theoretical contribution offered here. We conclude with a summary and discussion of theoretical implications and potential extensions.

STRATEGIC RESEARCH SITE: FORENSIC DNA ANALYSIS LABORATORIES

The objective of this research is to identify and describe the mechanisms leading to social tie formation between corporate agents that lead to knowledge diffusion between macro-social entities. We thus require a strategic site in which tasks are inherently complex and require more than codified instructions—that is, a context in which knowledge is embedded in both individual actors and the specific social systems in which they work (on organizational knowledge see, e.g., Cook and Brown 1999; Tsoukas and Vladimirov 2002). We also require a setting in which knowledge is constantly changing, which implies that actors must constantly update their knowledge.

We identified an institutional field that evidenced these characteristics: government-run laboratories that analyze forensic DNA. The work of forensic scientists is knowledge-intensive, specialized, and highly complex, and it is subject to constantly changing technology (Self-identifying citation omitted).

The minimum educational requirement for forensic scientists² is a Bachelor of Science degree, and most scientists hold degrees in chemistry or biology. Many DNA analysts also have a Master of Science degree (often required for supervisory positions) in chemistry, biology, or forensic science. Supervisors often have doctorate degrees. Given the educational requirements and the subsequent task-specific human capital required, this field evidences many of the characteristics of science and academia as individuals must constantly update their knowledge and skills, and this learning process often occurs through networks and institutional mechanisms such as professional conferences.

There are DNA laboratories at the federal, state, and local levels. These labs are generally non-hierarchically arranged. State labs generally do not have authority over local labs, nor do federal over state labs. However, there are elements of hierarchy within the system with respect to: (1) the infrastructure (the FBI promulgates rules regarding access to the national database); (2) resources (e.g., lab funding); and (3) federal regulation.

Neither the size of a single lab nor the number of labs in a given state necessarily reflects the size (or population) of the host state. Rather, it is a result of historical development due to: state and local jurisdictions that attribute more or less importance to DNA analysis; institutional

² The field of forensic science is defined by the American Association of Forensic Scientists as “the application of the natural sciences to matters of the law.”

entrepreneurship (a successful lab is more likely to expand); and geographical necessity (states with greater land area may see the need for geographically dispersed labs).

Although procedural rules and regulations vary between labs and across jurisdictions, the core work of forensic scientists in government crime labs is essentially the same. It includes: determining the usefulness of a DNA sample provided by crime scene investigators; the preparation of a sample for analysis; the interpretation of DNA mixtures (e.g. when the DNA of two or more individuals is present in a sample); creating DNA profiles; and uploading the DNA profiles of convicted offenders into a database. The vast majority of procedures involved in these tasks are codified in painstaking detail in the labs' manuals, which are constantly updated to reflect the rapid change of technological advancement and resulting new procedures.

Furthermore, the FBI issues regulations that govern access to the Combined DNA Index System (CODIS). CODIS is software that links and operates local, state, and national databases of DNA profiles from convicted offenders, crime scene evidence from unsolved crimes, and missing persons. CODIS allows for the electronic comparison of these profiles. The objective of the database is to link known individuals to crimes, as well as crimes to each other. The state component of the database is known as the State DNA Index System (SDIS), where a subset of these profiles is also uploaded into the National DNA Index System (NDIS). Lab procedures are regularly audited under the auspices of the FBI to ensure compliance with standards set by the National Institute for Standards and Technology (NIST). Compared with private sector fields, this setting is thus one in which there are considerable pressures towards sharing (DiMaggio and Powell 1983). Inter-lab competitive forces for relationships should thus be subdued.

Despite this high level of codification, a considerable amount of ambiguity and discretion remains in the work of DNA forensic scientists. For example, the processing of DNA mixtures

requires interpretation. There are a number of statistical that can be used in similar cases, and different labs prescribe the use of different statistics (Butler 2005). Another example is the adoption of newly available technologies. In addition to decisions concerning what technology to use, there are different private equipment vendors to choose from with varying levels of quality and support. The choice of which vendors to use is thus consequential as it can significantly influence both the efficiency and efficacy of a lab. Finally, there is a wide range of discretionary management issues ranging from human resource issues to decisions concerning the design of new laboratory space.

In summary, DNA laboratories in the United States offer a good site within which to study knowledge sharing across salient macro-structural boundaries: First, there is a rather limited and clearly definable population of laboratories (about 180), with at least one laboratory in every state; second, each laboratory, and individuals within laboratories, have significant discretion concerning boundary spanning and sharing activities; and, third, each lab's ability to fulfill its responsibilities is contingent on constantly acquiring and internalizing new knowledge.

QUALITATIVE AND QUANTITATIVE DATA COLLECTION AND ANALYSIS

Qualitative data collection. DNA labs exhibit variation in terms of size, location, structure, and expertise. To ensure that we developed a comprehensive understanding of the field of enquiry we sampled firms across various strata. Respondents for this study were selected through purposeful sampling (Yin 1994) according to the professional roles held by members of the community in a single case study design with multiple sites. This method of sampling allows for comparability between the respondents while allowing for variation across labs types to achieve representativeness.

Participant recruitment began with state CODIS administrators. We assumed that these individuals had a greater need to connect to their peers in other labs because there is only one

CODIS administrator per lab, and CODIS is the mechanism used for inter-state sample comparisons. After a first round of telephone interviews, two of the authors attended several CODIS conferences and interviewed state administrators in-person. Attending these conferences allowed the authors to gain insights into the interaction patterns of CODIS administrators. Early participants in the study led us sequentially to additional important respondents within the community (Miles and Huberman 1994). We stopped recruiting additional respondents when we started getting very similar responses and therefore had reached saturation in our sample. Our final pool of respondents consisted of 33 individuals, from 30 labs and 26 states.

We conducted semi-structured, open-ended interviews with these informants that lasted between thirty minutes and two hours. The interviews covered the following topics: Description of work function and work environment; knowledge required for the job; sources of knowledge; and nature, extent, and methods of community engagement. As our data collection proceeded, we also included specific questions about the nature of ties to individuals in other labs. Table 1 below provides a description of the qualitative interviewees. For more detail on data acquisition see (self-identifying citation omitted).

Insert Table 1. about here

In addition to the aforesaid data collection efforts, two of the authors visited several crime labs and observed forensic scientists in their places of work. These were not full-fledged ethnographies. However, the observers were nonetheless able to get a far richer appreciation of the localized settings, inter-lab variations in culture and practice, and work functions of scientists in different labs (Emerson, Fretz, and Shaw 2001).

Qualitative data analysis. The analytic process was driven by the objective of making sense of the data by identifying recurring patterns. To this end, we followed the coding and analysis process described in Miles and Huberman (1994). All interviews were transcribed verbatim, coded, and interpreted by the authors and a team of research assistants. Throughout the data analysis process, we followed a procedure of iterating between our conceptual framework, the data, and the literature (Strauss 1987).

All interviews were transcribed verbatim, and coded: First, each of our qualitative research team members “open coded” the interview transcripts as they became available and labeled meaningful passages. Second, we then met as a team and discussed each label, resulting in an initial list of codes (Miles and Huberman 1994). This list of codes was used by a team of research assistants to subsequently code all interviews with the help of the qualitative research software. Trained research assistants were instructed to code line by line; thus the smallest coding unit was a single line of text. Each member of the research team also wrote memos or notes about codes and their relationships, which became part of the data. One author periodically met with the team of research assistants and discussed issues that arose during individual coding. Once the initial coding was complete, a senior research assistant ran a comparison of coding to ensure intercoder reliability; 85% of the codes were similarly identified by different coders. This is considered an acceptable level of inter-coder reliability (Smith, Feld, and Franz 1992).

Discrepancies between the individual coders were discussed until an agreement was reached. The third step entailed axial (or pattern) coding. This entails subsuming similar codes into meta-codes (Miles and Huberman 1994). For example, we clustered all codes that referred to the way individuals search for knowledge, what sources they turn to, and the rationales behind those choices, into a meta-code entitled “search strategies.” Finally, fourth, we constructed

matrix displays (Miles and Huberman 1994) to study the relationship between meta-codes and select characteristics of the respondents.

Survey data. Surveys were administered to representatives of DNA labs in the United States in December of 2005. Complete responses were received from 37. By implication we did not receive responses from all states. Consequently, in Table A1 in the Appendix we tabulate and test for differences between responding and missing states. Descriptive results suggest that, on average, states that did respond tend to be larger and have more lab facilities and capacity than those that did not. However, differences are not statistically significant.³

We then supplemented the survey data with external data from each state from government sources. These external data include population and economic statics and dynamics, geographic information, institutional (regional) affiliations, crime statistics, and information about forensic lab size, capacity, and prior assistance to other labs. Using data from government sources external to the survey mitigates concerns of common methods bias (Podsakoff, MacKenzie, Jeong-Yeon, and Podsakoff 2003). Table 2 below provides detail concerning each of the specific datum, its source, its mean and standard deviation.

Directed knowledge sharing ties across states. Survey participants were asked the following question to determine which labs in which states outside their own they contacted for assistance: “When your laboratory seeks additional expertise in difficult DNA cases (e.g., trace evidence, DNA mixtures, kinship analysis) in which labs are the individuals you would typically consult?” Respondents were asked to check next to each of the 50 US States and the District of Columbia if they contacted a lab therein for assistance. A dummy coded variable is thus specified such that ($X_{ij} = 0$ or $X_{ij} = 1$, but X_{ij} does not necessarily = X_{ji}). That is, assistance seeking

³ States for which we have consequential “missingness” include: Alaska, DC, Florida, Idaho, Kentucky, Maine, Michigan, Mississippi, Nevada, North Carolina, South Dakota, Tennessee, Washington, and Wyoming.

is construed as directed—lab i may seek the assistance of lab j but lab j need not seek the assistance of lab i .

Explanatory variables. Based on our initial qualitative and observational data collection we developed an appreciation for the importance of professional association meetings for establishing and maintaining contacts and accessing new knowledge. These meetings are foci (Feld 1981). *We thus expect to observe a positive relationship between the number of meetings that corporate actors of labs in different states both attended and the likelihood that a knowledge sharing tie exists between the states' labs.* To test this we compute a variable ranging from 0 to 6 (mean = 3.658; SD = 1.473) denoting the number of various professional conferences scientists in labs i and j both attended in the past two years.

We should observe that laboratories in adjoining states such as New York and New Jersey are more likely to have a directed knowledge sharing tie than New York and Alabama. One reason for this is the movement of personnel between laboratories, as indicated in our qualitative data analyses. Moreover, adjoining states are more likely to have collaboration opportunities as a result of regional crime patterns (Stouffer 1940; Brantingham and Brantingham 1981; Canter and Gregory 1994; Harries 1999). It thus follows that to the extent that offenders commit crimes in other jurisdictions (states) than those in which they reside, they are more likely to do so in: (a) adjacent states, and/or (b) jurisdictions that are closer. Consequently, labs are more likely to have DNA hits for offenders in adjacent or close states, and are thus more likely to have knowledge sharing ties with such labs. *We thus expect that laboratories in different states are more likely to have knowledge sharing ties with laboratories in other states as a function of proximity* (see, e.g., Sorenson and Stuart 2001; Kalnins and Chung 2006). A dummy variable denoting states i and j are adjacent is thus calculated (mean =

0.09; SD = 0.286). We also create vectors of measures to capture location differences and those pertaining to similarity across other characteristics. For geography we include (ln) distance (mean = 6.772; SD = 0.809); and dummy variables indicating that states i and j are in the same Census region (mean = 0.234; SD = 0.424) or Health and Human Services Region (mean = 0.089; SD = 0.234) respectively.

From a functional perspective, labs in states with a greater capacity to assist with investigations should be more likely to be contacted by other states' labs for assistance. We thus compute measures that get at each state's labs' capacity to assist with investigations. These measures include global mean-centered measures of the number of: investigations state j 's labs assisted in 2003 ($\#(\text{investigations aided})_{j, '03} - \Sigma \frac{\#(\text{investigations aided})_{m, '03}}{N}$), forensic samples ($\#(\text{forensic samples})_{j, '03} - \Sigma \frac{\#(\text{forensic samples})_{m, '03}}{N}$), and offender profiles ($\#(\text{offender profiles})_{j, '03} - \Sigma \frac{\#(\text{offender profiles})_{m, '03}}{N}$) in j 's databases.

To capture preferential attachment or a Matthew Effect (Yule 1925; Merton 1968; 1985; 1988; Havemann, Heinz, Wagner-Döbler 2005) we include a measure of each alter states' labs indegree that is centered around the global mean: $I(\text{deg})_j - \Sigma \frac{I(\text{deg})_m}{N}$. This mechanism implies that net of functional differences accounted for with the measures outlined above, *we should observe that labs in given states (i) are more likely to seek counsel from labs in different states (j) if other states (m) also seek counsel from j .*

We also calculate measures that vary over ego and alter dyads concerning the relative crime and economic conditions in each state to measure similarities (homophily) and differences in the states' crime, social, and economic conditions that may compel one state's labs to seek counsel from labs in another state. These measures include: differences in per capita income

between states i and j at time $t-1$ ($|\text{Per capita income}_{i, '04} - \text{Per capita income}_{j, '04}|$); comparative changes in population growth rates between states from $t-2$ to $t-1$ ($|\Delta(\% \text{ pop. growth})_{i, '03-'04} - \Delta(\% \text{ pop. growth})_{j, '03-'04}|$); the absolute difference in the number of hate crimes ($|\# \text{ hate crimes}_{i, '04} - \# \text{ hate crimes}_{j, '04}|$), comparative changes in murder rates ($|\Delta(\% \text{ murders})_{i, '03-'04} - \Delta(\% \text{ murders})_{j, '03-'04}|$), and rapes ($|\Delta(\% \text{ rapes})_{i, '03-'04} - \Delta(\% \text{ rapes})_{j, '03-'04}|$). We focus on these crimes because of their relative prominence, as well as the importance of DNA evidence in apprehending and convicting perpetrators in such cases. We also calculate similar metrics specific to each alter state, j ($\# \text{ hate crimes}_{j, '04}$, $\Delta(\% \text{ murders})_{j, '03-'04}$, $\Delta(\% \text{ rapes})_{j, '03-'04}$), based on the intuition that states with higher rates of these crimes may receive more public exposure. These metrics are all lagged based on the nature and availability of the data. The length of the respective lag of each measure is noted in table 2 below, along with a description of the measure along with its source. Finally, as a structural control, we specify a dummy variable indicating reciprocity ($X_{ij} = X_{ji} = 1$), which occurs quite rarely in our data (mean = 0.009; SD = 0.094).

 Insert Table 2. about here

Statistical model. We use quantitative data to determine which factors lead a lab in a specific state to contact a lab in a different state for counsel and advice on difficult cases. Modeling this process is complicated because of structural autocorrelation arising from the dependency between observations in the same row or column (Krachhardt 1988). We thus employ an MRQAP model (a linear probability model in this context) that is robust to multicollinearity and skewness using the double semi-partialling method proposed by Dekker, Krachhardt, and Snijders (2007). P-values are computed using 2000 – 3000 permutations.

PRESENTATION OF FINDINGS

Insert Figure 2. about here

The social structure of inter-state DNA lab knowledge sharing

Figure 2 is a graphical depiction of the digraph. Some basic descriptive statistics of the digraph indicate one large component and one isolate (South Carolina). The average geodesic distance (among reachable dyads) is 3.287. The mean raw (normalized) indegree is 2.622 (7.282), with a standard deviations of 2.654 (7.373). These figures indicate that most states do not have a significant amount of contact with labs in other states, but there are a few labs that seek or provide counsel to several other states. Outdegree (indegree) network centralization is 29.63% (23.92%), which suggests that directed ties are not concentrated around a few hubs. Finally, measures of centrality indicate that states such as California, Texas, Illinois, and Pennsylvania are frequently cited as states housing labs to which labs in other states turn to for counsel with difficult cases. The state of Virginia has the largest indegree. In order to determine what factors lead to these ties, we turn now to the regressions.

Insert Table 3. about here

Table 3 above presents coefficients from MRQAP linear probability regressions. The first model includes variables measuring propinquity and geography. As noted above, because crimes tend to be perpetrated within close proximity to offenders' homes (Stouffer 1940; Brantingham and Brantingham 1981; Canter and Gregory 1994; Harries 1999), it follows that to the extent that offenders commit crimes in other jurisdictions (states) than those in which they reside, they are more likely to do so in: (a) adjacent states, and/or (b) states that are geographically closer based

on distance. Consequently, labs should be more likely to have DNA hits for offenders in adjacent or close states, and should thus more likely to have knowledge sharing ties with such labs. Our quantitative evidence substantiates this intuition. Sharing a border with a state (adjacency) increases the probability of also seeking counsel from a DNA lab in that states ($b = 0.184$; $SE = 0.178$; $p < .001$ (two-tailed test)). Similarly, if a state lab is in the same Census region as that of another state it is also more likely to seek counsel from a lab in that other state ($b = 0.031$; $SE = 0.121$; $p < .1$). On the other hand, (ln) distance between states decreases this likelihood ($b = -0.019$; $SE = 0.081$; $p < .1$). Figure 4 below depicts a potential reason for this pattern that is consistent with the story outlined above. The figure illustrates the number of DNA “hits” in Massachusetts’ that can be matched to those in other states. Most of the hits are concentrated in the Northeast in states that are adjacent to Massachusetts.

Insert Figure 4. about here

The primary source of social connections and knowledge transfer—mentioned by nearly every one of our informants in the qualitative interviews—is attendance at several different professional meetings. Co-attendance at professional meetings is important for several reasons. First, it affords the opportunity to deepen and broaden existing social relationships. Second, it provides a venue for the exchange of best practices and emerging knowledge. Finally, meetings are a focus (Feld 1981) or setting (Sorenson and Stuart 2008) where new ties can form—ties that may extend beyond geographic areas.

Models 2 and 3 include the measure of the number of professional meetings representatives of labs in states i and j both attended. Model 2 is an unconditional model and model 3 includes the measures of propinquity and geography. The results of both models

indicate that as the number of meetings i attended that j also attended increases, so too does the probability that i seeks help from j in difficult cases (model 2: $b=0.016$; SE = 0.037; model 3: 0.014; SE = 0.086; both $p < .05$).⁴

Among the most consistent findings in the various literatures concerning networks is that they tend to exhibit power-law distributions (Barabási and Albert 1999; Newman 2005; Clauset, Shalizi, and Newman 2009). These distributional realizations may be the result of preferential attachment processes or a Matthew Effect (Yule 1925; Merton 1968; 1985; 1988; Havemann, Heinz, Wagner-Döbler 2005). In our context such processes imply that a lab in state i is more likely to seek counsel in difficult cases from labs in state j (but not necessarily vice versa) if that lab is more frequently contacted by other labs (m) for advice. This may be due to past performance differences or those pertaining to perceptions thereof. An example of the essence of this process playing out in our research site is recounted by a deputy director in a NY lab, who was asked about who he contacts for information. His response is telling: “Usually it’s a telephone call or an email to colleagues that I know. I find the information is more the opposite. [i.e., people usually contact NYC rather than vice versa].” Model 3 includes a measure of indegree for state j . The estimate suggests that states (i) are indeed more likely to seek counsel from labs in another state (j) if other states’ labs (m) also seek counsel from labs in state j ($b = 0.025$; SE = 0.078; $p < .001$).

Functional differences and perceptions thereof may not be tightly coupled (Merton 1968). Our quantitative data allow for a nice distinction of the two. We have data on directed (indegree), as just noted. Additionally, we have quite granular data on the economic, social, and criminological characteristics of different states. We also collected data on each state’s lab-

⁴ A squared term could not be estimated along with the main effect due to excessive collinearity.

specific capabilities (number of samples, offender profiles) and prior level of investigations aided that enable us to directly measure and thus distinguish states' labs actual ability and past willingness to assist with investigations. Not surprisingly, these coefficients are correlated with an "alter" (j) lab's indegree: .70 with the number of offender profiles; .67 with the number of forensic samples; and .70 with the number of investigations aided. These correlations suggest that directed ties seeking counsel on hard cases are indeed informed by the ability and willingness of a target lab to offer assistance. There is, however, an important and sizeable effect that cannot be attributed to these functional concerns that implicates other processes.

In model 5 we specify an unconditional model that includes three measures that capture state j 's functional capacity and past willingness to assist with DNA cases. The evidence suggests that labs are more likely to contact labs in other states for assistance if they have evidence that state has a greater than average willingness to aid in investigations. The same is true if it has a larger than average number of offender profiles. However, once the other measures are included (in model 6) these effects no longer achieve statistical significance at conventional levels. Estimates in model 6 also suggest that the comparative crime, economic, and social conditions of the states does not have a bearing on the likelihood of seeking assistance across states. Finally, there is strong evidence that labs are likely to seek counsel on difficult cases from labs that seek counsel from them ($b = 0.786$; $SE = 0.061$; $p < .001$). That is, there is strong tendency towards reciprocity.

The quantitative evidence provides a picture of the social structure of state-run DNA laboratories in the United States in and around 2005. It also describes what factors are associated with assistance seeking across states. Results indicate that propinquity and geography matter. Having a place to meet and socialize also matters, as does preferential attachment. These data do

not, however, afford leverage to open the black-box of tie formation. We now turn to the qualitative evidence that does.

Search for knowledge

Analytical technologies constantly evolve. As a result, scientists in the labs we studied are compelled to constantly update their knowledge. In coding the qualitative responses we observed a consistent pattern concerning the sequence of knowledge search: technicians first reviewed documents (internal manuals, audit documents, and professional websites). If this search failed to yield answers, they would then seek the counsel of experts within their labs on the matter. For example, Bob*⁵, an assistant in a NY lab, put it:

[...] we have a chain of command, if I had a question, or a concern about a policy that I feel like is not in existence for example, like the manual doesn't address something, and I've never been trained in how to address something, so I would go to [supervisor's name excluded] first. Although, I kind of know in the back of my head, she's not going to know the answer to this, or she doesn't have the discretion to decide, okay, you're right, there's no policy, this is the policy. She's going to have to take my question to [leader's name removed] who's the technical leader [...]

This was more frequently the case in the largest labs that had the most internal resources. It also serves as a meaningful baseline when interpreting other findings. That is, a knowledge search process that begins by referring to codified material.

Figure 1 provides a stylized depiction of how individual organizational actors (employees) develop social capital that: (1) spans organizational boundaries; and (2) links laboratories, thus allowing knowledge and assistance flow. This figure is based on the qualitative evidence from our case as well as prior research.

⁵ This and all other names are pseudonyms.

Social capital formation

The primary source of social connections and ultimately knowledge transfer—mentioned by nearly every one of our informants—is attendance at professional meetings. This co-attendance can lead to knowledge transfer and the establishment of individual, scientist-level ties between labs that are otherwise unlikely given the geographic distance and size differences of labs; for example, an inter-organizational link between a large lab in NY and one in a small state established by individual scientists. As Jonah of a NY lab states:

[...] No, I mean the social aspects can't be ignored. That's one of the biggest perks of going to those things. But going to the conferences and listening to the lectures and seeing the post presentations, and seeing what people are doing out there is amazing, 'cause there are some people in these Podunk little college towns that are doing forensic research that is cutting edge stuff and it's great. We see these posters and we're blown away. And we come back here and we say listen, we have to call that guy and talk to him about his, whatever he developed, protocol, procedures, whatever, and see if we can implement that in this laboratory 'cause it's feasible, we can do that.

Professional association meetings are thus an important focus (Feld 1981) in which relationships form and strengthen. Consequently, lab administrators use them strategically—an investment in sociability (Bourdieu 1985; Lin 1991) that leads to social capital. Claire, a CODIS administrator stated it thusly:

We had 2 people at that meeting. I try and send as many people as I can to conferences like that. Not just to listen to the papers, but also it's a good way to meet up with everyone else in the other labs and share stories and get information. So yeah, we attend as many conferences as we can.

John, a deputy director, also stresses the social aspect of meetings

But if people have met at meetings—what I find in the meeting, it's not always the content that's important, but also the contacts that I make, they're both important. I meet my colleagues at these various meetings, and then we network at the meetings. So I find I get as much out of dinner, lunch and talking to people as I do for the scientific sessions. And

that's not to say the meeting's not important for scientific sessions, because I don't want to be quoted that way.

It is important to note that many of the meetings are funded by either the government or commercial vendors who sell the analytical technologies used by the scientists. This funding makes it possible for many of the scientists to attend the conferences who might not otherwise be able to. This institutional structure is thus a vital force that helps foster the conditions for social tie formation and subsequent knowledge diffusion across labs.

Micro social mobility and macro knowledge flow: The important of audits and employee mobility

Prior research has revealed how champions such as consultants are often the conduits of the diffusion of new practices (e.g., Covalleski and Dirsmith 1988; DiMaggio 1991; Sitkin, Sutcliffe, and Schroeder 1994). Our fieldwork suggests a similar mechanism: institutional audits.

Institutional audits are a particularly interesting basis of knowledge transference across organizations. Audits are typically conducted by seasoned individuals in the field. When they visit a site they thus serve multiple purposes. First, they serve a role of auditor by evaluating laboratories. In the process they also afford access to their stocks of knowledge gleaned from their own site and the other sites they have visited. Second, a visit to a site affords the opportunity for an interpersonal connection (much like academic talks and subsequent one-on-one faculty meetings). These connections can serve as the link connecting two laboratories across states that serves as a conduit for knowledge transfer across space. Cathy describes this process thusly:

I think we have one of the most thorough training programs in the country, and I base that on audits of other laboratories, and I've done about 50 audits of different laboratories. There's another source of contacts that I have and a good base knowledge of who does what. That helps me out a lot there, those audits. I always go to the experienced people first. And I have experiences in some areas and I'm able to answer those questions, but areas I don't, I try to find people and identify people when I go out to

meetings that have experiences in areas that I don't 'cause I can't be experienced in every area; there's just not enough time in the day.

Prior research shows that the localization or movement of individuals (micro social units of analysis) across salient macro-social divides has a significant bearing on the concentration, distribution, and diffusion of knowledge. This transfer can occur when employees or owners from one firm make lateral moves to other firms, or found their own firms (Argote and Ingram 2000; Phillips 2002; Song, Almeida and Wu 2003). For example, the interorganizational mobility of scientists can lead to the localization of knowledge within macro-level social boundaries such as regions (Saxenian 1994; Almeida and Kogut 1999; Rosenkopf and Almeida 2003). Structural rules that inhibit this movement can thus have implications for knowledge flows across organizations (Marx Strumsky, and Fleming 2009). Similarly, the mobility of individuals can also lead to the dissolution of the linkages among macro social entities. The movement of professionals from one firm, A, to another, B, for example, often leads to the dissolution of an existing business relationship between firms (e.g., between A and C) as manager, i, moves from firm B to firm C (see, e.g., Broschak 2004; see also Baker, Faulker, and Fisher 1998). We also find that inter-organizational and inter-state knowledge transfer originates from the movement of colleagues across labs. Brandon, a DNA tech leader, put it thusly:

Well it comes in one of two groups, and that's folks that I came to know personally, by working with them. Two of my former bosses are on that list. Actually I guess three of my former bosses are on that list. [...]

SUMMARY & CONCLUSIONS

Significant attention has been devoted to the patterns and consequences of boundary spanning activities, information search and sharing, and isomorphism of organizational knowledge and practice. In much of this research organizations are viewed as social actors in and of themselves that engage in this boundary spanning activity. This focus is sensible when

analyzing the patterns of organizational ties. However, it is not especially well-suited to the study of the mechanisms governing how and why organizations develop social capital and span boundaries in the first place. In this research we unpacked the black box of organizational social capital formation boundary spanning activity. By using unique qualitative and quantitative data from a knowledge intensive industry—US government crime laboratories involved in DNA analysis—we identified several mechanisms leading to boundary spanning activity. The quantitative data we provide a picture of several of the mechanisms, as well as the antecedents of isomorphism processes. Results reveal that structural features, chance meetings, and the initiative of lab leaders (and to a lesser extent subordinates) lead to boundary spanning activity, access to distinct pools of knowledge, and, ultimately, isomorphism. Thus social structure exhibits significant subtleties. On one hand, structural forces clearly contour and condition the nature of knowledge flow across organizational boundaries. Institutional forces create the conditions for tie formation by providing funding for scientist travel to professional conferences, or by dictating the timing and actors involved in institutional audits. However, this funding does not, in itself, lead to tie formation. That requires the action of individuals in pursuit of knowledge.

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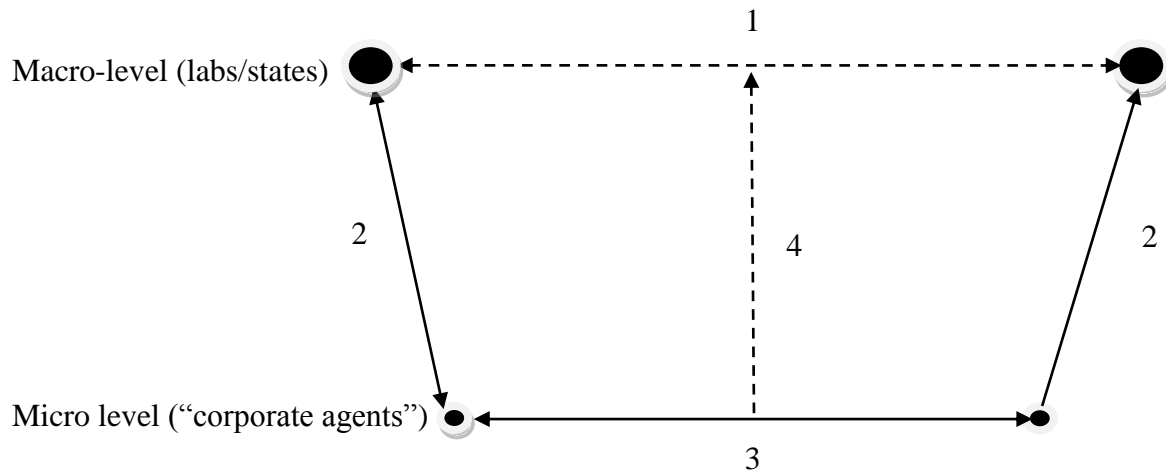
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FIGURE 1. STYLIZED DEPICTION OF INTERPLAY BETWEEN LEVELS OF ANALYSIS



Note:

1. Mechanisms (e.g., contracts, trade) linking macro social entities
2. Mechanisms linking macro social entities to micro entities (e.g., employment contracts)
3. Relationships between micro social entities
4. Link between macro social entities enabled by micro level (corporate agents)

FIGURE 3. STATES WEIGHTED BY NUMBER OF DNA MATCHES WITH SAMPLES FROM MASSACHUSETTS

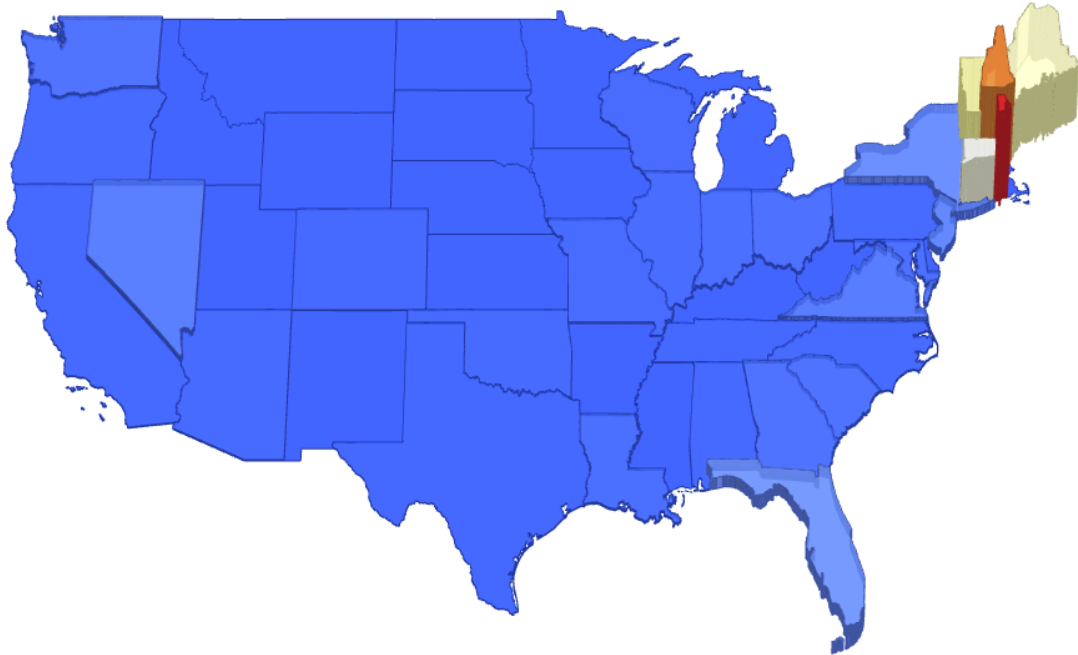
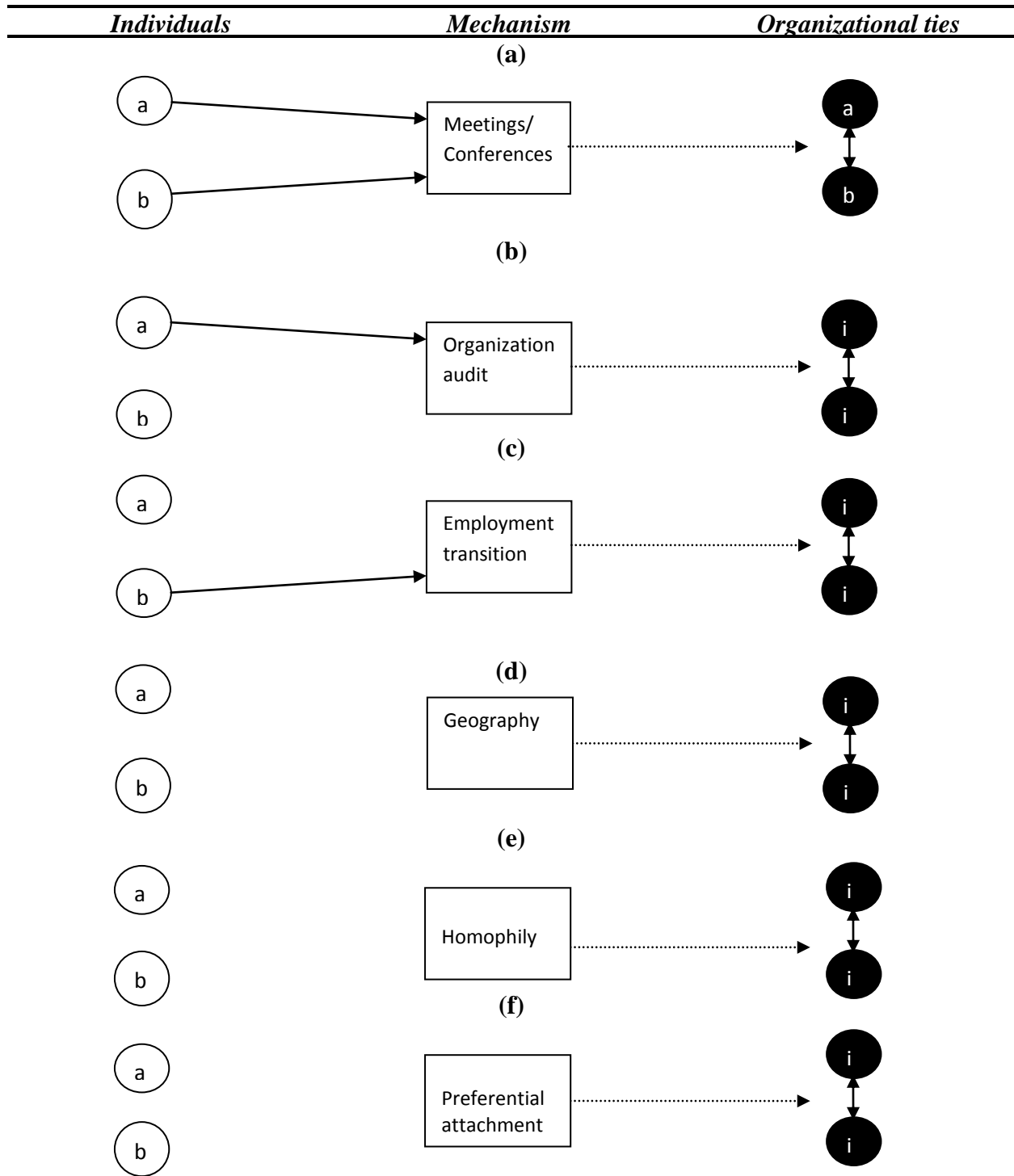


FIGURE 4. STYLIZED DEPICTION OF MECHANISMS LEADING TO KNOWLEDGE DIFFUSION



Note: Mechanisms “A,” “B,” and “C” identified in our field work; mechanisms “D,” “E,” and “F” identified in prior literature and our quantitative analyses. Lowercase *a* and *b* represent individual corporate actors (e.g., CODIS administrators); *i* and *j* denote labs.

TABLE 1. OVERVIEW OF INTERVIEWS CONDUCTED

<u>Professional role*</u>	<u>Affiliation: State lab</u>	<u>Affiliation: Local lab</u>	<u>Total</u>
Lab director	8	2	10
Technical leader	7	3	10
CODIS administrator	8	5	13
Total	23	10	33

* In cases where individuals hold multiple roles, the highest-ranking role is indicated.

TABLE 2. DESCRIPTION OF KEY VARIABLES

<u>Variable</u>	<u>Mean</u>	<u>S.D.</u>	<u>Year</u>	<u>Source</u>
<i>Knowledge sharing tie between states</i> $(i \rightarrow j, j \rightarrow i, X_{ij} \neq X_{ji})$	0.073	0.260	2005	Survey
Σ professional meetings employees of states <i>i</i> and <i>j</i> co-attended.....	3.658	1.473	2003 – 2005	Survey
Reciprocity ($X_{ij}=X_{ji}=1$).....	0.009	0.094	2003 – 2005	Survey
$I(\text{deg})_j - \Sigma \frac{I(\text{deg})_m}{N}$	0.000	2.761	2003 – 2005	Survey
State <i>j</i> 's capacity to assist with investigations:				
$\#(\text{investigations aided})_{j, '03} - \Sigma \frac{\#(\text{investigations aided})_m, '03}{N}$	0.000	1210.919	2003 – 2004	FBI Uniform Crime Reports/ DOJ/FBI/CODIS
$\#(\text{forensic samples})_{j, '03} - \Sigma \frac{\#(\text{forensic samples})_m, '03}{N}$	0.000	4174.435		
$\#(\text{offender profiles})_{j, '03} - \Sigma \frac{\#(\text{offender profiles})_m, '03}{N}$	0.000	117495.945		
Comparative and state-specific dynamic $ (i - j) $ crime environments:				
$ \# \text{ hate crimes}_{i, '04} - \# \text{ hate crimes}_{j, '04} $	210.33	299.667		
$ \Delta(\% \text{ murders})_{i, '03-'04} - \Delta(\% \text{ murders})_{j, '03-'04} $	17.121%	26.294%		
$ \Delta(\% \text{ rapes})_{i, '03-'04} - \Delta(\% \text{ rapes})_{j, '03-'04} $	10.108%	10.492%		
$\# \text{ hate crimes}_{j, '04}$	165.243	255.359		
$\Delta(\% \text{ murders})_{j, '03-'04}$	-0.608	16.485		
$\Delta(\% \text{ rapes})_{j, '03-'04}$	1.773	10.162		
Comparative state economic and population metrics:			2003 – 2004	Regional Economic Information System, Bureau of Economic Analysis, US Department of Commerce
$ \text{Per capita income}_{i, '04} - \text{Per capita income}_{j, '04} $	\$5,495.79	\$4,149.43		
$ \Delta(\% \text{ pop. growth})_{i, '03-'04} - \Delta(\% \text{ pop. growth})_{j, '03-'04} $	0.631%	0.55%		
Geography and institutional measures:				
State-to-state distances (LN distance).....	6.772	0.809	2005	GIS
States <i>i</i> and <i>j</i> share a border (i.e., are adjacent).....	0.090	0.286	2005	U.S. Census
States are in the same Census region.....	0.234	0.424	2005	U.S. Census
States are in the same Health and Human Services region.....	0.089	0.284	2005	U.S. Dept of Health and Human Services

Note: Italicized variables are dichotomous (0/1). Statistics calculated at the state or dyadic level (indicated by “survey”).

TABLE 3. MRQAP REGRESSION COEFFICIENTS PREDICTING DIRECTED TIES BETWEEN DNA LABS IN STATES *I* AND *J*

MODEL:	1.	2.	3.	4.	5.	6.	7.
	Propinquity	Co-attendance at meetings	Propinquity + Co-attendance	Indegree	Functional Considerations	States' crime, Economic, and Population trends	Final model
VARIABLE:			b(SE)	b(SE)	b(SE)	b(SE)	b(SE)
	b(SE)	b(SE)					
<i>States i and j are adjacent</i>	0.184*** (0.178)		0.181*** (0.14)	0.176*** (0.124)			0.135*** (0.212)
<i>States are in same Census region</i>	0.031# (0.121)		0.033* (0.095)	0.036* (0.083)			0.02 (0.204)
LN(Distance) between states <i>i</i> and <i>j</i>	-0.019# (0.081)		-0.019# (0.083)	-0.016 (0.068)			-0.016# (0.203)
Σ of meetings <i>i</i> and <i>j</i> co-attended.....		0.016** (0.037)	0.014* (0.086)	0.011* (0.083)			0.009* (0.184)
Reciprocity ($X_{ij}=X_{ji}=1$).....							0.786*** (0.061)
$I(\text{deg})_j - \Sigma \frac{I(\text{deg})_m}{N}$				0.025*** (0.078)			0.024*** (0.197)
$\frac{\#(\text{investigations aided})_j, '03}{\Sigma \frac{\#(\text{investigations aided})_m, '03}{N}}$					0.000* (0.031)		0.000 (0.203)
$\frac{\#(\text{forensic samples})_j, '03}{\Sigma \frac{\#(\text{forensic samples})_m, '03}{N}}$					-0.000 (0.031)		-0.000# (0.202)
$\frac{\#(\text{offender profiles})_j, '03}{\Sigma \frac{\#(\text{offender profiles})_m, '03}{N}}$					0.000** (0.031)		0.000# (0.200)
$\frac{\# \text{ hate crimes}_{i, '04} - \# \text{ hate crimes}_{j, '04}}{N}$						0.000 (0.056)	-0.000 (0.187)

$ \Delta(\% \text{murders})_{i, '03-'04} -$ $\Delta(\% \text{murders})_{j, '03-'04} \dots\dots\dots$						-0.000 (0.05)	0.000 (0.21)
$ \Delta(\% \text{rapes})_{i, '03-'04} -$ $\Delta(\% \text{rapes})_{j, '03-'04} \dots\dots\dots$						-0.002** (0.04)	-0.000 (0.206)
Per capita income $_{i, '04} -$ Per capita income $_{j, '04} \dots\dots\dots$						-0.000** (0.039)	-0.000 (0.191)
$ \Delta(\% \text{ pop. growth})_{i, '03-'04} -$ $\Delta(\% \text{ pop. growth})_{j, '03-'04} \dots\dots\dots$						-0.022# (0.043)	-0.014 (0.197)
Intercept.....	0.180	0.014	0.123	0.116	0.072	0.013	0.138
R ²	0.072	0.008	0.078	0.151	0.038	0.017	0.234
Adjusted R ²	0.070	0.008	0.076	0.148	0.036	0.014	0.227
Probability	0.000	0.012	0.000	0.000	0.000	0.000	0.000
# of permutations	2000	2000	2000	2000	2000	2000	3000
# of observations	1332	1332	1332	1332	1332	1332	1332

Source: Unique data; see table 2 above for a description of the data sources.

Note: Unstandardized coefficients presented. MRQAP computed via Double-Dekker Semi-Partialling. *Italicized* variables are dichotomous (0/1).

#P < .05 (one-tailed test)

*P < .05 (two-tailed test)

**P < .01 (two-tailed test)

***P < .001 (two-tailed test)

APPENDIX

TABLE A1. EVALUATION OF POTENTIAL SAMPLE SELECTION

VARIABLE	RESPONSE		MISSING RESPONSE		<i>t-test p value</i>
	<i>Mean</i>	<i>SE</i>	<i>Mean</i>	<i>SE</i>	
Population, 2004.....	6,241,057	1,154,646	4,481,164	1,297,474	0.312
Δ population, '03-'04.....	0.810	0.097	1.162	0.298	0.279
Δ % murder, '03 - '04.....	-0.608	2.748	4.943	6.982	0.469
# of hate crimes, '04.....	169.833	43.504	109.643	39.885	0.314
# of labs in state.....	3.865	0.764	2.357	0.589	0.125
# of offender profiles, '03.....	84,070.46	19,582.66	61,727.14	25,408.78	0.492
# of forensic samples, '03.....	3513.27	695.739	2128.143	900.487	0.233
# of investigations aided, '03.	922.514	201.82	642.357	370.03	0.513
<i>N</i>	37		14		

Sources: See table above for sources of each measure.

Note: T-tests performed assuming equal or unequal variance (more liberal results shown, i.e., those more likely to evidence a difference). States (+DC) for which we have consequential “missingness” include: Alaska, DC, Florida, Idaho, Kentucky, Maine, Michigan, Mississippi, Nevada, North Carolina, South Dakota, Tennessee, Washington, and Wyoming.

#*P* <.1 (two-tailed test)

**P* <.05

***P* <.01

****P* <.001

TABLE A2. ROBUSTNESS CHECKS: MRQAP REGRESSION COEFFICIENTS PREDICTING DIRECTED TIES BETWEEN STATE *I* AND *J*'S DNA LABS

Model	Description	Key estimates, b(SE)	Model	Notes
A1	Model 1 w/ HHS regions instead of Census regions	0.018(0.118), ns	MRQAP	
A2	Model with attributes of <i>i</i> : $\Delta(\# \text{ rapes})_{i, '03-'04}$ $\# \text{ hate crimes}_{i, '04}$ Per capita income $_{i, '04}$	-0.000(0.025), ns -0.000(0.031), ns 0.000(0.033), ns	MRQAP	
A3	Model with attributes of <i>j</i> : $\Delta(\# \text{ rapes})_{j, '03-'04}$ $\# \text{ hate crimes}_{j, '04}$ Per capita income $_{j, '04}$	0.000(0.012), ns 0.000(0.019)* 0.000(0.023), ns	MRQAP	
A4	Model 7 with $\# \text{ hate crimes}_{j, '04}$	-0.000(0.054), ns	MRQAP	All other coefficients consistent with underlying model