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# Status and collaboration: The case of pro bono network inequalities in corporate law☆

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ABSTRACT

We examine how status shapes intersectoral collaboration between large US corporate law firms and public interest legal organizations (PILOs). We draw from status theories to derive competing hypotheses about the status processes that generate organizational collaboration within this network. Supporting a status-signaling hypothesis, high-status law firms tend to collaborate with similarly high-status pro bono organizations. This gives rise to a highly unequal playing field where a handful of PILOs have a wealth of connections to high-status law firms, while the majority of PILOs only collaborate with few –relatively under-resourced– non-high-status firms. We test our hypotheses using latent space models for weighted networks. We further validate our results using more traditional QAP multiple regressions. In closing, we discuss the implications of our findings for scholarship on status and organizations, as well as the role that corporate law firms play in exacerbating inequality in terms of access to justice in the US.

## 1. Introduction

Similar to the broader nonprofit sector, public interest law organizations (PILOs) have insufficient resource capacity to meet the demand for their services, leading them to secure resources from a patchwork of various sources (Albiston and Nielsen, 2014).[1] Most notably, large-firm pro bono assistance has emerged as the major mechanism for providing access to the legal system for poor and other marginalized individuals via PILOs (Cummings, 2004; Daniels and Martin, 2009; Boutcher, 2017). Professional rules within the legal profession currently mandate that lawyers provide 50 hours of pro bono legal services per year, with large law firms collectively donating millions of attorney hours toward otherwise unmet legal needs (Boutcher, 2017). Many large law firms may choose to work with the same PILOs, thereby creating an unequal playing field of highly networked PILO "winners" and isolated PILO "losers" (Brulle, 2000; Boutcher, 2013) or, put simply, network inequality. What law-firm factors are linked to this network inequality, where law firms tend to send corporate lawyers providing pro bono services to the same PILOs? Moreover, does the status of law firms, specifically, play a key role in shaping the flow of pro bono to PILOs?

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[1] We use the term public interest law organization (PILO) broadly in order to capture the range of nonprofit organizations that receive pro bono assistance from large law firms to fulfill their missions, namely, provide legal assistance to the poor and other marginalized individuals. These organizations range from traditional legal services and legal aid groups that deal with individual legal matters to impact litigation groups that focus on specific legal causes (e.g., ACLU, NAACP).

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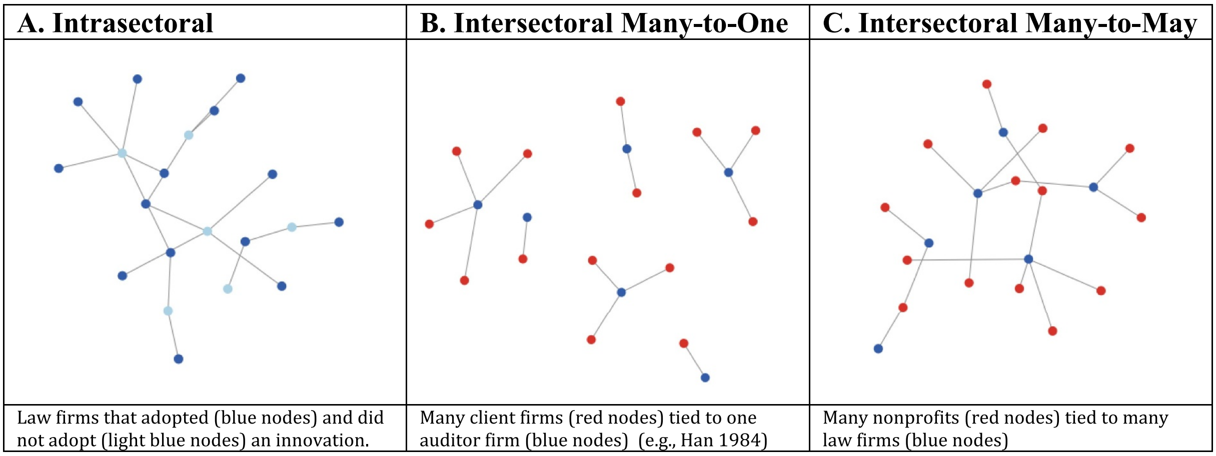


**Fig. 1.** Archetypical interorganizational networks.

In this research, we examine the extent to which pairs of large law firm donors exhibit isomorphic patterns of pro bono (i.e., ties to similar PILOs) and draw on signaling theory to develop expectations about how status matters. We argue that high-status law firms may get prioritized by PILOs, thus producing isomorphism where the former tend to work with the same PILOs. This latitude may not be equally granted to actors from middle- and low-status categories, however. We employ latent space models for weighted networks to investigate whether law firms of similar status are more likely to have isomorphic pro bono ties. Our key contribution is highlight how firm status acts as a force structuring intersectoral collaborations between for-profit and nonprofit organizations.

### 1.1. *Status and intersectoral networks*

Fig. 1 shows archetypes of relationships that have been studied in the literature on status and interorganizational networks. Panel A in Fig. 1 represents a one-mode (intrasectoral) network, by far the most common type of study in this literature. Here, institutional researchers typically study the diffusion of a single innovation through an interorganizational network with many organizations that belong to the same sector (DiMaggio and Powell, 1983). Researchers have applied this insight to examine how networks promote similar patterns in the adoption of specific organizational practices, such as total quality management (TQM) programs (Westphal et al., 1997), ISO 9000 certification (Guler et al., 2002), protest tactics (Wang and Soule, 2012), and the design of CEO compensation packages (Davis and Greve, 1997). In these accounts, interorganizational networks provide key pathways for diffusing a specific organizational practice through a population of organizations, thereby making connected organizations more similar (i.e., isomorphic) over time.

There has been less attention to intersectoral networks. Panel B in Fig. 1 represents an intersectoral network where many firms in one sector select, based on their status, one and only one firm in a different sector (*intersectoral, many-to-one relationships*). Here, the work of Han (1994) on client-auditor relationships is an exemplar. Finally, Panel C in Fig. 1 depicts the case where many organizations in one sector select many organizations in another sector (*intersectoral, many-to-many relationships*). To the best of our knowledge, Podolny' (2001) study on the relationships between entrepreneurial start-ups and venture capital firms is the only study that has examined how status shapes many-to-many (intersectoral) relationships, that is, how status structures the selection of multiple third-party organizations (e.g., entrepreneurial start-ups) by multiple focal organizations (e.g., venture capital firms). This is critical because these networks are highly prevalent from an empirical point view (Saavedra et al., 2009; Kitts et al., 2016). Since this paper analyzes the role of status in the emergence of pro bono ties between elite law firms and nonprofits, it directly contributes to a better understanding of how firm status shapes patterns of intersectoral ties, particularly to the nonprofit sector.

The existing scholarship suggests that pro bono is an arena in which status competition amongst large law firms plays out. Daniels and Martin (2009) found that pro bono is used to attract and retain top legal talent, burnish a firm's image and brand through visible gifts of time and money, develop relations with deep-pocketed clients, and factor directly into firm rankings, such as those produced by *Vault* and *American Lawyer*. Indeed, pro bono activities by firms are used as a “shorthand” by both law students, lawyers, and clients (Daniels and Martin: 155–156). Critically, it is important to note that law firms control the resources, which are donated to PILOs and other nonprofits. Following resource dependency accounts, nonprofits are active in bringing law firm partners onto their boards. This suggests the primacy of law firm status, as opposed to the status of PILOs.

### 1.2. *Conceptual framework*

We draw on the status-signaling perspective (Granados and Knoke, 2013; for a review, see Sauder et al., 2012), which has focused on how status provides benefits to organizations. The status-signaling perspective is typically framed in terms of how status is used as a noisy, often decoupled signal for quality. Because quality is often unobservable, network ties become a key mechanism to make relational claims about status. In this context, organizations are expected to capitalize on their status in networks to generate economic benefits.

A key argument of classic signaling theory is that the value of a given signal for high quality should be correlated with the costs associated with producing that signal (Spence, 1973). Critically, when signaling is costly, actors at the top of a given status hierarchy are highly incentivized to publicize their quality by signaling in order to separate themselves from comparatively lower status actors (Feltovich et al., 2002; Gambetta, 2009). Here, the classic example is Veblen's analysis of conspicuous consumption practices by elites.

However, when signaling costs are relatively low, and therefore affordable for comparatively low status actors, high-status actors should engage in counter-signaling (nonconformity) since publicizing their quality can actually be interpreted as a sign of insecurity in their positions (Bellezza et al., 2014). In these situations, high-status actors seem to be able to (re)produce their position in the social hierarchy by actively avoiding signaling. Feltovich et al. (2002: 631) offer several examples like the following: "People of average education show off the studied regularity of their script, but the well-educated often scribble illegibly. Mediocre students answer a teacher's easy questions, but the best students are embarrassed to prove their knowledge of trivial points." Signaling theory thus predicts that actors at the top of a status hierarchy would exhibit nonconforming behaviors depending on whether or not other actors have the resources to conform, that is, to pay the costs of signaling their quality. In sum, high signaling costs incentivize signaling by high-status actors, whereas low signaling costs permit middle and sometimes low-status actors to signal while high-status actors may refrain.

We argue that signaling costs are indeed high in pro bono since there are clear opportunity costs for any law firm that diverts billable hours to pro bono, especially beyond the number of hours required by the normative standards in the profession.[2] Law firms are, however, motivated to signal high status to external audiences, including clients, law schools, law students, courts, and regulatory agencies (Daniels and Martin, 2009: 155-56). Furthermore, and drawing on the core status-signaling argument that the choice of partner is in itself a signal of quality (Podolny, 1994), PILOs will also be motivated to establish relationships with high-status law firms to signal their own status (Podolny, 1994; Han, 1994); thus, we propose the following hypothesis:

**H1.** Pairs of high-status firms will be more likely to work with the same PILOs, compared to pairs of firms that are not high status.

### *1.3. Middle-status conformity*

Middle-status conformity theory provides an alternative hypothesis about the pattern of ties between law firms and PILOs. With its origins in social psychology, the middle-status conformity (**MSC**) argument posits an inverted U-shaped pattern of conformity as a function of status, where actors with comparatively high or low levels of status have lower levels of conformity with the expected norms and conventions in a given field (Phillips and Zuckerman, 2001). The MSC argument is that higher status actors, being secure in their status, can afford nonconformity with their status-peers, whereas comparatively lower status actors engage in nonconformity as a practice of rebellion or deviance in relation to referents in the middle of a given status hierarchy. The latter actors, in contrast, can neither afford high-status nonconformity, nor defy conventions by counter-signaling due to the threat of status loss.

We believe the case of pro bono work among large corporate firms fits the scope conditions for MSC theory, as specified by Phillips and Zuckerman (2001). First, we use public rankings of law firms to index status beliefs (Correll et al., 2017). Our approach is similar to recent research showing how law school public rankings generate status advantages for highly ranked schools (Espeland and Sauder, 2016). Second, we distinguish status from class by separately accounting for firms' social position (status) and class/revenue. Finally, we highlight that the practice this paper focuses on (pro bono services) is indeed relevant for law firms' identities and for the ethos of the profession more generally (Cummings, 2004; Sandefur, 2007).

Critically, we argue that MSC theory is implicitly embedded in a signaling perspective that assumes that actors in the middle ranks of a given status hierarchy can indeed afford conformity (i.e., signaling). In a word, when signaling costs are relatively low, actors in the middle of a given status hierarchy can indeed pay the costs of signaling; thus, explaining why MSC theory expects nonconforming behaviors from high-status actors, we argue. This implies the following competing hypothesis, which assumes the provision of pro bono is affordable for middle-status firms:

**H2.** Isomorphism in pro bono ties between law firms will take the form of an inverted U-shaped curve where firms in the middle ranks of a given status hierarchy will have higher levels of isomorphism than firms at the top or bottom of the status hierarchy.

## 2. Methods

This research focuses on the population of 100 largest corporate law firms in the United States during 2005. We identified the largest law firms based on the 2005 *Vault Law 100 Ranking* (Vault, 2005) and the 2005 *American Lawyer 200 Ranking* (American Lawyer, 2005). We then merged this list with the *Vault Guide to Large Firm Pro Bono Programs* (Vault, 2006), which included information on pro bono programs and firm practice areas among 137 large firms for 2004 and 2005. Our measure of firm status was based on the 2005 *Vault Law 100*. This is a published ranking, based on status perceptions of practicing attorneys, of the one hundred most prestigious U.S. law firms. All the control variables were obtained from the 2005 version of the *American Lawyer 200* (*Am Law*).

[2] According to Rule 6.1 of the American Bar Association's Model Rules of Professional Conduct: "Every lawyer has a professional responsibility to provide legal services to those unable to pay. A lawyer should aspire to render at least (50) hours of pro bono *publico* legal services per year."

Our analytic sample included 84 U.S.-based large law firms, which were included across all three data sources (i.e., *Vault Law 100, American Lawyer 200,* and *Vault Guide to Large Firm Pro Bono Programs*). We also conducted sensitivity analyses on a larger sample of 132 firms, or 66 percent of the largest 200 law firms based on the Am Law 2005 rankings and pro bono data (see Appendix for details), but present the results based on the *Vault* ranking because this is a better measure of status.[3] The results from these larger sample based on the *Am Law* rankings were consistent with the results presented here.[4]

Following Mizruchi and Marquis (2006), dyads are the best unit of analysis to study organizational networks when the outcome variable (i.e., similarity in pro bono ties) and predictors are relational. We therefore restructured our firm-level data as dyadic data, such that each observation represented a specific pair of firms, and variables tapped similarity or difference between pairs of firms. As a result, there are 3,486 law-firm dyads ([84*(84-1)]/2) under analysis in this paper. Descriptive statistics for firms and dyads are presented in Table 1.

### 2.1. Dependent variable

*Similarity in pro bono ties*. In the *Vault Guide to Large Firm Pro Bono Programs*, law firms were asked the following item: "List up to 10 organizations for which your firm performed pro bono legal services in 2004 and 2005." Based on this item, we constructed a two-mode matrix (**A**) of pro bono organizations (*o*) by firms (*f*), denoted as $\mathbf{A}_{o \times f}$, which we then transformed into a firm-by-firm matrix ($\mathbf{B}_{f \times f}$), where each cell indicated, for a pair firms, the pro bono organizations that both worked with. The transformation of $\mathbf{A}_{o \times f}$ was accomplished via the projection formula (Breiger, 1974):

$$\mathrm{B}_{f\mathrm{X}f} = (\mathrm{A}_{\mathrm{oX}f})^T \cdot \mathrm{A}_{\mathrm{oX}f} \tag{1}$$

To measure firm similarity in pro bono ties, we computed the Jaccard similarity index for each dyad. This index assessed the number of shared collaborative ties between any two firms as a component of the total ties possible across each of the two firms in the dyad. More formally, the equation for the Jaccard similarity index between the *i*th and *j*th *firm* is equal to:

$$\mathrm{J}_{ij} = \frac{\mathrm{D}ij}{\mathrm{D}ij + \mathrm{D}i + \mathrm{D}j} \tag{2}$$

where $\mathrm{J}_{\mathrm{ij}}$ is the Jaccard similarity index between firm *i* and firm *j*. $\mathrm{D}_{ij}$ is the number of pro bono clients shared by firm *i* and firm *j*, $\mathrm{D}_i$ is the number of unique pro bono organizations connected to firm *i,* and $\mathrm{D}_{\mathrm{j}}$ is the number of unique pro bono organizations tied to firm *j*. The index ranges from 0 (no overlapping ties to pro bono clients between firms *i* and *j*) to 1 (complete overlap between firms *i* and *j*). Since all pairs of firms are included in the calculation, the result of computing the Jaccard index for all elements in $\mathbf{B}_{f \times f}$ is a new weighted undirected sociomatrix $\mathbf{J}_{f \times f}$ that represents dyadic similarity (i.e., isomorphism) in pro bono ties for all dyads present in the pro bono network $\mathbf{B}_{f \times f}$. For ease of interpretation, each entry of the matrix $\mathbf{J}_{f \times f}$ was multiplied by 100.

### 2.2. Key independent variable

*Dyadic firm status*. As mentioned above, our status measure for firms was based on the law firms listed in the *Vault Law 100* rankings, which were ranked based on a survey of 14,052 law firm associates. Following Phillips and Zuckerman (2001), who also studied large corporate law firms, we constructed a firm-status measure with three categories: high-, middle-, and low-rank firms. The first category of the dyadic-status variable, highly-ranked dyads (hereafter, high-status dyads), was comprised by pairs of firms in which both were ranked among the top 25 firms in the *Vault* Ranking. The second category, mid-ranked dyads (middle-status dyads), only contained pairs of firms that were between the 26th and 75th ranks. The final category was for lower-ranked dyads (low-status dyads) – that is, cases in which both firms were between the 76th and 100th position in the context of the *Vault* rankings. For completeness, we developed two additional status categories across the dyads. The first one contains dyads in which there was a one-status difference between firms (e.g., firm *j* was high-status while firm *i* was middle-status or firm *j* was middle-status while firm *i* was low-status). The second category contains dyads in which there was a two-status difference between firms (i.e., firm *j* was high-status and firm *i* was low-status). High status dyads were selected as the reference category in all statistical analyses.

We conducted extensive analyses to generate a qualitative, empirically-grounded, categorization of dyadic status based on the original firm-level *Vault Law 100* data. This approach was needed because it was not clear where the cut-off points for status categories (i.e., high-, mid-, and low-ranked actors) existed within a particular field. OLS regressions were used to test for the association between dyadic similarity ($\mathbf{J}_{f \times f}$) and different dyad-based qualitative status classifications.[5] The goodness-of-fit of each model was assessed through the BIC. Results consistently suggested three different status categories using the above mentioned cut off

[3] Although the *Am Law* rankings increase our sample size significantly, these rankings are simply a function of firm gross revenues. Because the *Am Law* measure of status is confounded with performance and class (i.e., revenue), we decided to use the *Vault Law 100* data, which is based on status perceptions of practicing attorneys.

[4] There are two strong reasons in favor of the validity of our research design: first, since we are mainly interested in analyzing the role of status in the emergence of intersectoral collaborations, the publicity of status beliefs is a necessary factor to incorporate into the analysis (Correll et al., 2017; see also Espeland and Sauder, 2016). The *Vault* and *Am Law* rankings are by far the most widely (i.e., publicly) known sources to proxy the status of large law firms in the US. Second, it should be noted that elite law firms are far more likely to be the key players shaping the field of pro bono collaborations in the US, which is the center of our substantive concerns.

[5] See the Appendix for more details.

**Table 1**
Dyad-level and firm-level descriptive statistics.

| Dyads | | | Firms | | |
|---|---|---|---|---|---|
| | **Mean/Percent** | **SD** | | **Mean/Percent** | **SD** |
| Jaccard index | 48.46 | (20.64) | | | |
| Status | | | Status | | |
| High | 7.3% (253) | | High | 27.4% (23) | |
| Middle | 27.1% (946) | | Middle | 51.2% (43) | |
| Low | 3.9% (136) | | Low | 21.4% (18) | |
| One status difference | 50.5% (1760) | | *Total* | 100.0% (84) | |
| Two status difference | 11.2% (391) | | | | |
| Total | 100.0% (3486) | | | | |
| Pro bono hours difference | 26.36 | (22.32) | Avg. Pro bono hours per lawyer | 56.46 | (24.43) |
| Revenue difference (ln) | 19.15 | (1.20) | Revenue (ln) | 19.96 | (0.56) |
| Size difference | 448.58 | (454.0) | Size | 725.42 | (451.26) |
| Age difference | 48.00 | (35.18) | Age | 94.12 | (42.08) |
| Gender difference | 5.62 | (4.21) | Percent female | 36.77 | (4.96) |
| Race difference | 4.20 | (3.54) | Percent minority | 13.77 | (3.71) |
| Diff. In number of practice areas | 10.17 | (8.50) | Number of practice areas | 16.38 | (9.37) |
| Headquarter location | | | Headquarter location | | |
| Different cities | 88.16% | | Not in New York City | 70.24% | |
| Same cities | 3.24% | | New York City | 29.76% | |
| New York City | 8.61% | | | | |

points. As reported in the Appendix, however, the key findings of this paper do not depend on the specific values of these cut off points.

### 2.3. Control variables

Based on existing literature (Uzzi and Lancaster, 2004; Phillips and Zuckerman, 2001; Tinkelman and Mankaney, 2007), we controlled for a number of organizational variables in our models. All continuous variables were computed as the absolute difference between the values for the two firms in a given dyad. To tap firm-size differences, we computed the absolute difference in total number of lawyers between firms in each dyad. Other continuous variables included as dyadic controls were as follows: differences in revenue, differences in pro bono hours, differences in year of establishment (i.e., firm age), differences in number of practice areas, differences in percent female lawyers, and differences in percent minority lawyers. In addition to these continuous controls, we created two dummy variables for geographical location. The first indicated for each dyad whether both firms were headquartered in the same city, excluding New York City; the second was a dummy for pairs of firms located in New York City. Dyads with firms headquartered in different cities were coded as the reference category.

### 2.4. Latent space modeling

To examine whether firm status was associated with similarity in pro bono ties, we employed latent space modeling (Hoff et al., 2002), a modeling technique appropriate for analyzing network data that is undirected as well as weighted. Originally, the latent space model was developed to account for unobserved homophily in (latent) social space (Krivitsky et al., 2009). This modeling strategy is critical for this paper since the outcome matrix under analysis ($\mathbf{J}_{f \times f}$) is indeed a weighted matrix. The latent space model assumes that a given outcome network (e.g., $\mathbf{J}_{f \times f}$), and the (weighted) ties between actors it contains ($\mathbf{J}_{ij}$), occur with a probability that depends on actors' distances from each other in a k-dimensional latent social space (Hoff et al., 2002; Handcock et al., 2007; Hoff, 2005). The key idea is that nodes with small (large) distances in the latent social space should also have small (large) distances in the observed network (e.g. $\mathbf{J}_{f \times f}$). Therefore, it is assumed that the observed network provides critical information about the underlying social distance between each pair of nodes *i* and *j*.

Latent space models assume that once dyadic distances in (latent) social space are properly derived, then the set of all dyadic observations (i.e., the network matrix under analysis) can be modeled through a dyadic generalized linear model (Hoff, 2005; Krivitsky et al., 2009; Cranmer et al., 2017). More formally, using the notation of Cranmer et al. (2017), the probability of observing the network matrix **N** under the latent space modeling framework takes the following form:

$$\mathrm{P(N|Z,X,\theta)} \prod_{i \neq j} P(Nij|\boldsymbol{z}i, \boldsymbol{z}j, \boldsymbol{x}ij, \theta) \tag{3}$$

This means that the observations $\mathbf{N}_{ij}$ in the network matrix **N** are conditionally independent given their specific positions $z_i$ and $z_j$ in latent space, a vector of dyadic covariates $\mathbf{x}_{ij}$ and their respective parameters $\boldsymbol{\Theta}$. Latent space models were fitted using the R package *latentnet*, version 2.8 (Krivitsky and Handcock, 2008). This software effectively allowed us to control for network dependencies by conditioning on dyadic positions in an unobserved Euclidian space (Handcock et al., 2007). In particular, the dyadic similarity associated with each dyad in $\mathbf{J}_{f \times f}$ was modeled using distribution and link functions that were normal. The latent space models featured in this paper were implemented using Bayesian inference in the context of a Markov Chain Monte Carlo (MCMC) algorithm (Krivitsky and Handcock, 2008). Since there were not specific *a priori* expectations with regards to the particularities of the model being fitted, very small numbers (0.001) were used as priors for the two user-imputed parameters required by *latentnet*: scale and degrees of freedom of the variance of the dyad values. Every time a model was fitted, a burn-in of 400,000 full simulated networks was used; then, for the final sample, 50,000 new simulated networks were sampled from which we kept every one hundredth network.[6]

Given that the focus of this paper is on the relationship between dyadic status and dyadic similarity, the latent space model was an appropriate modeling technique for this relationship. This is the case because, unlike other advanced modeling alternatives that can also accommodate weighted network data, the latent space model does not require the specification of endogenous dependencies (e.g., triadic closure) behind the network data-generating process. As shown in the results section and in the Appendix, we also conducted sensitivity analyses by using a more traditional network modeling technique, QAP multiple regression (Dekker et al., 2007; Krackhardt, 1987; Cranmer et al., 2017), to test whether the main results were robust to our modeling approach.[7]

## 3. Results

Table 1 shows that the firms in our data are indeed large and established: firm size averages approximately 700 lawyers with average annual revenues of $466 million and an average of 16 practice areas. Similarly, the average firm was founded close to a century ago. About one third of firms are located in New York City and are primarily white (~75%) and male (~65%). In terms of the firm dyads, large corporate law firms show a relatively high level of isomorphism in pro bono ties. The mean for the Jaccard index is 48, which suggests that on average firms share about half of their pro bono client organizations. This figure is, however, less than both the density of the pro bono network (0.62) and the average degree (51.31), which are indicators of the overall number of ties in the network.

Fig. 2 presents a network visualization of the law firm-PILO network and shows a central cluster constituted by a substantial number of firms (purple) that work with the same pro bono organizations (red).[8] This central cluster is surrounded by a smaller number of firms that work with only one or two pro bono organizations that are also tied to another firm, with the remaining relationships appearing idiosyncratic. This network resembles a core-periphery structure, which has been reported before in studies of the legal profession (Faulkner, 1987; Paik et al., 2007) and is consistent with a pattern of PILO winners (connected to many firms) and PILO isolates. Fig. 2 also suggests that the national pro bono market among large law firms is highly integrated.

Table 2 provides descriptive statistics of the network shown in Fig. 2. From a total of 342 pro bono organizations, elite law firms collaborate with 50 of them, on average. Seen from the perspective of pro bono organizations, the average PILO in the network is connected to only 2.4 elite law firms. These numbers suggest that pro bono is indeed concentrated among a relatively small number of organizations. In essence, the descriptive results indicate a highly unequal distribution of pro bono ties among a relatively small number of organizations. This concentration is reflected in the high level of law firms' similarities in their pro bono ties, which we analyze next.

### 3.1. Latent space models

Table 3 presents parameter estimates from latent space models of pro bono dyadic similarity on status and control variables. BIC values indicate that the best-fitting model was Model 3. Model 1 provides an intuitive way to carry out a comparison of means by status after taking into account firms' position in (latent) social space. This model indicated that middle-status dyads ($b = -7.295$, $p < 0.001$), low-status dyads ($b = -2.307$, $p < 0.001$), and one-status-difference dyads ($b = -4.369$, $p < 0.01$) are each associated with lower average levels of similarity in their pro bono ties compared to high-status dyads. Two-status-difference dyads also exhibit a negative coefficient, but it is not statistically significant ($b = -1.121$, $p > 0.05$). These results suggest that the average level of dyadic similarity in pro bono ties exhibited by high-status dyads is between 2.3% and 7.3% higher than the level of dyadic similarity found in middle and low-status dyads. Importantly, the larger negative coefficient associated with the level of similarity of middle-status firms vis-à-vis high-status firms is indicative of middle-status *non*conformity in the pro bono ties network. As shown below, and in the Appendix, the key finding that non-high-status dyads in general, and middle-status dyads in particular, exhibit less similarity (i.e., isomorphism) in their network connections than high-status dyads do is robust to: (1) different modeling frameworks, (2) different specifications of the dependent variable; (3) different specifications of the key independent variables, and (4) different samples.

Model 3, the unrestricted latent space model, examines associations between dyadic similarity in pro bono ties and status, net of controls. This model shows little qualitative difference in the results, compared to Model 1. The one exception is related to the effect of two-status-difference, which does reach conventional levels of statistical significance. Indeed, Model 3 shows that middle-status dyads ($b = -3.881$, $p < 0.001$), low-status dyads ($-1.544$, $p < 0.05$), one-status-difference dyads ($b = -2.744$, $p < 0.001$), and two-status-difference dyads ($-1.775$ $p < 0.01$) are less isomorphic than high-status dyads.

In terms of the control variables, Model 3 shows that log revenue difference ($b = 1.101$, $p < 0.001$), pro bono hours difference

[6] For more details on specification and model setup see (Krivitsky et al., 2015).

[7] The Appendix reports how to access all the relevant materials to reproduce the results reported in this paper.

[8] This visualization was produced using the Fruchterman and Reingold force-drawing algorithm in the *sna* R package, version 2.4 (Butts, 2006).

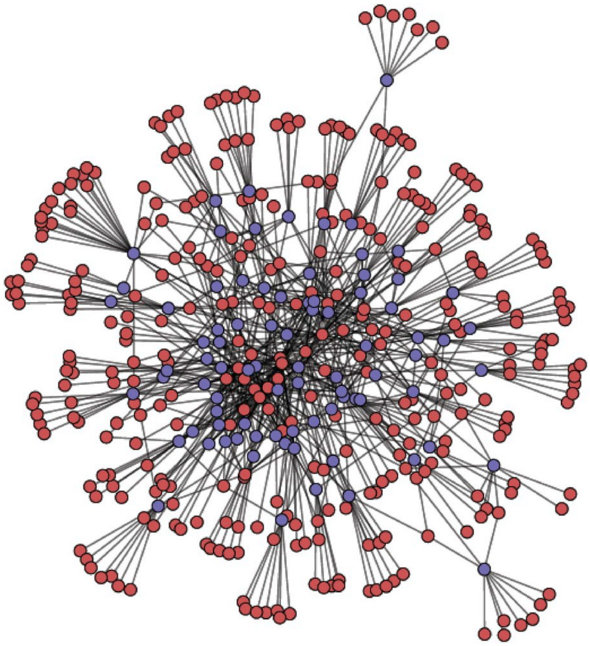

**Fig. 2.** Two-mode network visualization of law firms (purple) and pro bono client organizations (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

**Table 2**
Network-level descriptive statistics.

| | Statistic | SD |
|---|---|---|
| Number of nodes | 84 | |
| Number of ties | 2155 | |
| Number of isolates | 0 | |
| Graph density | 0.62 | |
| Mean geodesic distance | 1.37 | (0.51) |
| Maximum geodesic distance | 3 | |
| Mean degree | 51.31 | (15.76) |
| Normalized degree centralization | 0.27 | |

(0.021, $p. < 0.001$), age difference (0.009, $p. < 0.01$), race difference (0.137 $p. < 0.01$), and firms based in New York City ($b = 9.248$, $p. < 0.001$) are each associated with higher levels of similarity. It is worth noting the size of the New York City effect. This coefficient suggests a process of homophily generated by geographic propinquity: if both firms in a given dyad are located in New York City, they tend to be more similar than firms whose headquarters are located in any other two different cities. Model 3 also indicates that differences in terms of size ($b = -0.002$, $p. < 0.001$) are associated with lower levels of similarity.

In order to explore the robustness of the main findings, Model 4 in Table 3 presents the results of a QAP multiple regression using the same covariates as Model 3. Results from this new model indicate that middle-status dyads ($b = -15.965$, $p. < 0.01$), low-status dyads ($b = -15.741$, $p. < 0.05$), and one-status-difference dyads ($b = -11.360$, $p. < 001$) are indeed consistently associated with lower levels of dyadic similarity when compared to high-status dyads. These results mirror the results of the latent space model (Model 1 and Model 3 in Table 3), but among controls, only size difference and the New York City effect remain statistically significant.

Taken together, the evidence suggests that high-status dyads consistently have the highest level of similarity (i.e., conformity) in pro bono ties, a conclusion that does not appear to be mediated by any of the controls. These results are consistent with H1 and inconsistent with H2. Middle-status *non*conformity consistently emerges as a critical finding to explain (dis)similarity in pro bono ties of large corporate law firms in the U.S.

### *3.2. Network inequality: deepening the explanation*

Given the evidence suggesting prominent status-based network inequalities in the structure of pro bono ties, a key question remains: how does this map onto the opportunity structure for interorganizational exchange between elite law firms and pro bono organizations? To address this question, it should first be noted that PILOs are heterogeneous in terms of their actions and scope.

**Table 3**
Latent space models and double semi-partialing QAP regression for dyadic similarity (isomorphism) in pro bono ties.

| | Status Only | Controls Only | Unrestricted | Unrestricted |
|---|---|---|---|---|
| | LSM Model | LSM Model | LSM Model | QAP Model |
| | **(1)** | **(2)** | **(3)** | **(4)** |
| **Status (ref = high)** | | | | |
| **Middle** | −7.295 *** | | −3.881 *** | −15.965 ** |
| | [−8.452, −6.087] | | [-5.034, −2.719] | |
| **Low** | −2.307 *** | | −1.544 * | −15.741 * |
| | [-3.862, −0.712] | | [-3.079, −0.023] | |
| **One status difference** | −4.369 ** | | −2.744 *** | −11.360 ** |
| | [-5.352, −3.396] | | [-3.711, −1.782] | |
| **Two status difference** | −1.121 | | −1.775 ** | −7.537 |
| | [-2.101, −0.360] | | [-2.879, −0.666] | |
| *Controls* | | | | |
| Pro bono hours difference | | 0.029 *** | 0.021 *** | −0.041 |
| | | [0.018, 0.040] | [0.010, 0.033] | |
| Revenue difference (ln) | | 1.092 *** | 1.101 *** | −1.013 |
| | | [0.931, 1.257] | [0.939, 1.263] | |
| Size difference | | −0.002 *** | −0.002 *** | 0.001 |
| | | [-0.002, −0.001] | [-0.003, −0.001] | |
| Age difference | | 0.124 *** | 0.009 ** | 0.014 |
| | | [0.006, 0.019] | [0.003, 0.016] | |
| Gender difference | | 0.007 | 0.037 | −0.090 |
| | | [-0.056, 0.083] | [-0.030, 0.114] | |
| Race difference | | 0.186 *** | 0.137 ** | −0.017 |
| | | [0.110, 0.262] | [0.061, 0.211] | |
| Diff in # of practice areas | | −0.048 * | −0.036 | −0.0237 |
| | | [-0.084, −0.012] | [-0.072, −0.001] | |
| Headquarter (ref = diff city) | | | | |
| New York City | | 10.062 *** | 9.248 *** | 23.964 *** |
| | | [9.125, 10.992] | [8.323, 10.187] | |
| Same cities | | −0.242 | 0.585 | 0.641 |
| | | [-1.606, 1.778] | [-0.745, 1.951] | |
| Constant | 77.094 *** | 49.111 *** | 52.140 *** | 80.287 *** |
| | [76.109, 78.103] | [45.996, 52.159] | [48.979, 55.295] | |
| N (dyads) | 3486 | 3486 | 3486 | 3486 |
| Number of permutations | – | – | – | 2000 |
| BIC (LSM) or Adj $R^2$ (QAP) | 24331.37 | 24206.96 | 24030.39 | 0.190 |

*p < 0.05, **p < 0.01, ***p < 0.001. QAP Estimation performed in *sna* 2.4; LSM estimation performed in *latentnet* 2.8.

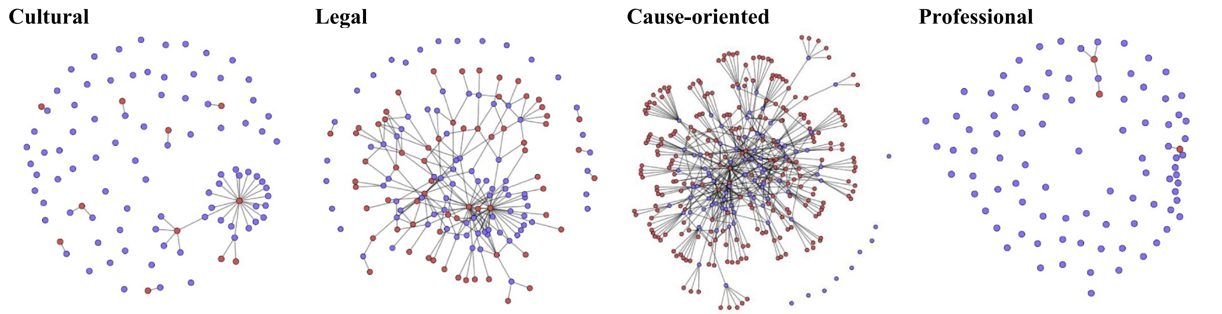


**Fig. 3.** Network visualization of law firms (purple) and pro bono client organizations (red) by client category. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Fig. 3 plots four affiliation (i.e., two-mode) networks of law firms by PILOs based on the classification developed by Boutcher (2013): cultural clients (e.g., Boys Choir of Harlem), legal services clients (e.g., Legal Aid Society), cause-oriented clients (e.g., Lawyers for Children in America), and professional association clients (e.g., Women's Bar Foundation). This is important because corporate law firms in the U.S. could be systematically tied to pro bono client organizations that tend to belong to specific sectors irrespective of their status. We expect that the network inequalities reported in Table 3 are a systemic, rather than a sector-specific, phenomenon.

Fig. 3 clearly shows that legal service clients and cause-oriented clients are the two main types of pro bono organizations in the data at hand. Based on this information, Models 1 and 2 in Table 4 show results where the original fully-specified latent space model (Model 3, Table 3) was fitted to the legal services subgraph and the cause-oriented subgraph separately. In addition, we fitted these

**Table 4**
Robustness checks: Double semi-partialing QAP for dyadic similarity (isomorphism) in pro bono ties for relevant PILO sectors.

| | Cause-Oriented | Legal Services |
|---|---|---|
| | **Model (1)** | **Model (2)** |
| **Status (ref = high)** | | |
| **Middle** | −16.066 ** | −17.893 ** |
| **Low** | −10.000 | −15.998 |
| **One status difference** | −10.553 ** | −12.173 ** |
| **Two status difference** | −4.848 | −7.159 |
| *Controls* | | |
| Pro bono hours difference | 0.007 | −0.007 |
| Revenue difference (ln) | −0.983 | −0.583 |
| Size difference | −0.001 | −0.004 |
| Age difference | 0.013 | 0.034 |
| Gender difference | 0.155 | −0.428 |
| Race difference | −0.147 | −0.030 |
| Diff in # of practice areas | −0.185 | −0.257 |
| Headquarter (ref = diff city) | | |
| New York City | 20.957 *** | 45.828 *** |
| Same cities | 2.718 | 0.478 |
| Constant | 67.697 *** | 40.200 ** |
| N (dyads) | 2775 | 2211 |
| Number of permutations | 2000 | 2000 |
| Adjusted $R^2$ | 0.200 | 0.264 |

*p < 0.05; **p < 0.01; ***p < 0.001. QAP Estimation performed in *sna* 2.4.

two new models using QAP multiple regressions to make sure that our findings were not a mere artifact of the latent space modeling framework. Coefficient signs support the results reported in Table 3, corroborating our main conclusions based on both the full network and the latent space modeling framework. The results for low-status dyads do not reach conventional levels of statistical significance, however. This is not fully unexpected since the analysis of these two (sub)networks forced us to significantly reduce the original sample size used in the context of the full models presented in Table 3.

Based on this same 4-group classification of all pro-bono client organizations, Fig. 4 plots the number of unique connections (i.e., degree) between the 84 large law firms under analysis and the 342 pro bono organizations tied to them. The long tail that describes the number of connections in the full network (Fig. 4, panel A), and in the legal services (Fig. 4, panel B) and cause-oriented (sub) networks (Fig. 4, panel C), is indicative of the pervasiveness of the highly uneven opportunity structure for interorganizational exchange that the statistical analyses uncovered.

Take two different organizations in each main (sub)network as an example. In the cause-oriented category, ACLU is paired with a total of 27 out of 84 law firms (11 high status, 13 middle-status, and 3 low-status), while organizations like the Friends of Children with Special Needs is paired with only 1 low-status firm. Similarly, in the legal services category, an organization like the Legal Aid Society is paired with 27 law firms (13 high status, 10 middle-status, and 4 low-status), while the Legal Clinic for the Homeless is paired with 1 middle-status law firm. These patterns are indicative of the main structure of the network: on the one hand, there are a handful of clear pro bono client *winners* that have multiple collaborative relationships with several law firms. On the other hand, there are many pro bono client *losers* tied to a very low number of firms. These inequalities not only can be seen in the number of ties a given pro bono client organization has, but also, they actually can be translated into the number of pro bono hours available to nonprofits. This is true since, on average, high-status firms devote a total of 48,645 h in a given year to pro bono legal assistance (70.35 h per lawyer), while middle-status law firms devote 32,437 on average (53.08 h per lawyer), and low-status firms only devote 18,357 on average (44.12 h per lawyer). PILOs with ties to high-status firms thus have much better chances of accessing more hours

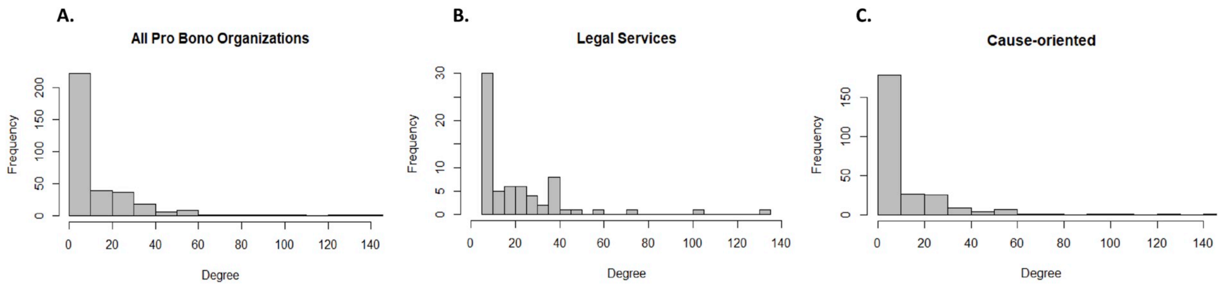


**Fig. 4.** Number of connections of pro bono client organizations to law firms.

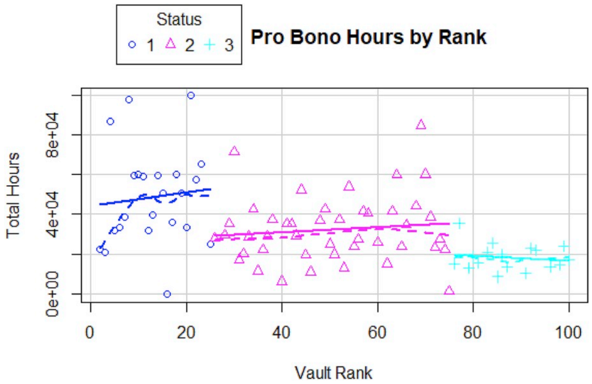


**Fig. 5.** Pro Bono Hours by Status, Lines represent total hours of pro bono work regressed on firms' position in the Vault rank (i.e., status 1 = high status; status 2 = middle status; status 3 = low status). Thinner lines represent (classic) linear regression lines, dotted lines represent non-parametric (smoothing) loess lines.

of pro bono legal assistance.

The average number of pro bono hours by status category further suggests that high-status actors are more willing to bear the opportunity costs of actively engaging in pro bono collaborations above the expectations in the profession, thus indicating that pro bono assistance can indeed be interpreted as a costly, rather than inexpensive, signal. Evidence in this regard comes from Fig. 5, where we plot the number of pro bono hours by status for all organizations in our sample. Fig. 5 clearly shows how the number of pro bono hours – which, we argue, can be interpreted as the opportunity cost of signaling – is a decreasing function of status. Put differently, Fig. 5 shows how high-status firms tend to devote a significant amount of resources to pro bono assistance, while middle-status (and low-status) actors are less willing and/or capable to do so. We note that this evidence is consistent with individual-level signaling models of charity that suggest that a motive for private charity among high-status individuals is the desire to demonstrate their distinctive quality (e.g., their wealth) vis-à-vis individuals of the same higher status (Glazer and Konrad, 1996; see also Bekkers and Weipking, 2011).

Knowing that in our sample high-status actors do tend to establish isomorphic ties with other high-status actors above and beyond key controls (see Table 3), Fig. 5 also supports a key prediction from the status signaling perspective: in the context of costly signals, high-status actors actively tend to signal in order to differentiate themselves from middle-status actors. We have shown in the statistical analyses that the tendency of high-status actors to signal is not indiscriminate, however. They tend to monopolize affiliations with the most sought-out PILOs; therefore producing high levels of high-status similarity in pro bono ties above and beyond key factors like geography, revenues, and size. This is consistent with the widely documented tendency of high-status organizational actors to establish ties with other high-status actors (Podolny, 1993, 1994; Granados and Knoke, 2013; Han, 1994).

The evidence presented in this article strongly suggests prominent inequalities in the access to pro bono legal assistance in contemporary United States. The evidence also suggests that these inequalities are augmented by status-based dynamics since high-status dyads tend to be more isomorphic than any other type of dyad. This uneven opportunity structure for interorganizational collaboration is, therefore, a prominent force that shapes both the structure of pro bono collaboration and access to justice in the US.

## 4. Discussion and conclusion

Our main finding is that elite law firms that co-occupy the highest status positions within the field are the most conforming in their pro bono relationships. These findings are true above and beyond key controls like organizational size and revenue (class). These results, therefore, support our status-signaling hypothesis where we argue that the closer actors are to the top of a given status hierarchy, the more likely they will build collaborative ties that mimic other high-status peers.

Why is this the case? Drawing from signaling theory, high-status firms may use their collaborative ties to PILOs as an imperfect, but symbolic signal for firm quality. Moreover, high-status firms may mimic the pro bono collaborative ties of their high-status peers as a means to reinforce their position within the field. High-status actors may be more "free" to select a wide range of relationships to nonprofits without taking a hit to their status. Actors farther down the status hierarchy may be less discerning in their ties, or lack access to expansive partnerships due in part to the high opportunity costs of pro bono work. This may be why we find that middle-status firms are the least similar to each other. It is possible that these firms are the most heterogeneous in their ability to secure relationships to nonprofits. Some middle-status firms may have access to the same organizations as high-status firms while others may lack access, leading this group to be diverse in their collaborations relative to each other.

This paper has important implications for the delivery of legal services and the "access to justice gap". Large law firms have become an important source of pro bono assistance to PILOs in an era of increasing resource scarcity. Although large firms have collectively mobilized millions of pro bono hours to assist a large number of PILOs, our findings raise important concerns with this model of legal assistance. Not all PILOs can generate the same number of collaborative ties with elite law firms. This generates a cumulative-advantage dynamic in which a reduced set of high-status law firms gets to collaborate with the same PILOs.

Finally, this paper has some limitations. First, since we employ cross-sectional data, a causal test of the processes described in this paper would need to rely on longitudinal network data. This limitation is particularly salient due to the lack of sufficiently developed methodological tools. Second, the present paper is also limited in its analysis of the diversity and complexity of both pro bono organizations and law firms. Even though we control for the number of practice areas each law firm has and we also conducted sensitivity analyses based on the two main pro bono (sub)networks (i.e., cause-oriented and legal assistance networks), future work should scrutinize the diversity and complexity of the organizations under analysis. It is possible, for example, that status-signaling dynamics are different depending on the organizational aims of pro bono organizations. Third, the question of whether the status of pro bono organizations matters was elided in this study. We lacked data on the relative status of PILOs, which were often more locally based than large law firms; nevertheless, it is possible that the relative rank of PILOs may impact their selection. This is a question for future research. Fourth, pro bono ties may result more directly from two-sided matching, where PILOs play a significant role in the selection of law firms. To the extent that PILOs are involved in the selection of law firms, additional mechanisms, such as two-sided signaling, may be relevant. This, we posit, would be an interesting question for future research. Fifth, a key scope condition of this finding is based on the fact that our theory is motivated by the assumption that public rankings carry relevant status signals that help coordinate actors' actions, including their collaborative efforts. In this regard, an empirical test of how and why public rankings are observed is beyond the scope of this paper. Finally, our findings are limited to the United States. Not all countries have a pro bono *publico* norm and not all countries have well-established public rankings to classify corporate law firms. Empirical analysis of contexts in which these conditions are not met would certainly be beyond the scope conditions of the theory developed in this paper.

## Appendix. Sensitivity Analyses

We conducted additional sensitivity analyses to examine the robustness of our results. First, we employed an alternative specification of the dependent measure that takes into consideration degree-based effects. Here, the fully-specified model (Table 3, Model 3 in the main article) was re-estimated using the inverse log-weighted dyadic similarity algorithm (Adamic and Adar, 2003). This measure of similarity calculates the number of common neighbors of the two firms in a given dyad weighted by the inverse logarithm of the degrees of those two firms. This estimation "is based on the assumption that two vertices [e.g., two law firms] should be considered more similar if they share a low-degree common neighbor, since high-degree common neighbors are more likely to appear even by pure chance" (Csardi and Nepusz, 2015:273). Results from this analysis, reported in Table A1, Model 1, show no qualitative difference when compared to the results in Table 3 Model 3, except because the low levels of isomorphism between both middle- (−24.062 $p. < 0.01$) and low-status dyads (−24.094 $p. < 0.01$) vis-à-vis high-status dyads is very similar. In general, however, these results suggest that the main findings of this paper are not a mere artifact of the particular specification of the dependent variable in general, or of degree-based (i.e., popularity-based) constrains in the opportunity structure for exchange in particular.

We also use an alternative measure of status available in the 2005 Am *Law* rankings. In this context, the fully-specified model was re-estimated using data from the American Lawyer (*Am Law*) rankings of 2005. Using the *Am Law* rankings introduce two major changes. First, the sample size increases from 86 firms to 132 firms (i.e., from 3486 to 8645 dyads). Second, and more importantly, status is measured using an entirely different source: the *Am Law* firm rankings. As can be seen in Table A1 Model 2, the main findings reported in this paper holds: non-high-status dyads, and *middle-status-dyads in particular*, are both consistently and significantly less isomorphic dyads than high-status dyads.

Finally, our results (see link below) show that increasing (reducing) the size of the middle-status category, and therefore, reducing (increasing) the size of the high- and low-status categories does not affect the main conclusions of this paper. The sensitivity analyses that were performed changed the size of the three status categories by increasing or reducing the size of the middle-status category from its original configuration (1st −25th/26th −75th/76th −100th), to the four following ones: 1st −10th/11th −90$^{th}$/91st −100th || 1st −20th/21st −80$^{th}$/81st −100th || 1st −30$^{th}$/31st −70$^{th}$/71st −100th || 1st −40$^{th}$/41st −60$^{th}$/61st −100th.

The code files to reproduce all results reported in this paper can be accessed here: https://github.com/diegoFLeal/probono. The data to reproduce the analysis are stored in the Mendeley data repository. A link will be provided by the publisher of the article.

Table A.1, Robustness Checks: Double Semi-Partialing QAP for Dyadic Similarity (Isomorphism) in Pro Bono Ties

| | Inverse Log-weighted | American Lawyer |
|---|---|---|
| | **Model (1)** | **Model (2)** |
| **Status (ref = high)** | | |
| **Middle** | −24.062 ** | −14.921 *** |
| **Low** | −24.094 ** | −26.204 *** |
| **One status difference** | −17.844 ** | −14.042 *** |
| **Two status difference** | −12.321 ** | −22.805 *** |
| *Controls* | | |
| Pro bono hours difference | −0.083 | 0.000 |
| Revenue difference (ln) | 0.100 | 2.138 *** |
| Size difference | −0.002 | −0.005 |
| Age difference | 0.031 | 0.011 |

| | | |
|---|---|---|
| Gender difference | 0.009 | −0.247 |
| Race difference | 0.020 | −0.164 |
| Diff in # of practice areas | −0.283 | −0.131 |
| Headquarter (ref = diff city) | | |
| New York City | 64.923 *** | 34.149 *** |
| Same cities | 3.985 | 7.679 *** |
| Constant | 48.593 *** | 5.802*** |
| N (dyads) | 3486 | 8646 |
| Number of permutations | 2000 | 2000 |
| Adjusted $R^2$ | 0.454 | 0.214 |

*p < 0.05; **p < 0.01; ***p < 0.001. QAP Estimation performed in *sna* 2.4.

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