Reproduction of Hierarchy? A Social Network Analysis of the American Law Professoriate

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Which individual has the greater lasting impact upon the path of American law: The median Supreme Court justice or an entrepreneurial law professor at an institution with a high degree of centrality? Given that we are inclined to support the former, we offer this provocative question not to provide a definitive conclusion but rather to encourage greater incorporation of the American legal academy in positive legal theory.

A growing body of work demonstrates that the perspectives held by these legal elites, in their position as both repositories and distributors of legal information, has consequences for American common law development. Specifically, while we believe additional empirical and theoretical work is needed, a deep relationship between the American legal academy and the development of American law has been highlighted in a variety of recent historical institutionalist scholarship. For example, leading scholars such as Brandwein and Graber offer compelling qualitative evidence linking members

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of the American legal academy, including Christopher Langdell, James Parker Hall and Zechariah Chafee, to the spread and/or survival of historically questionable legal narratives.[1]

The mounting record[2] raises serious questions about broader mechanisms supporting the development and reproduction of "historical truth."[3] In an effort to transition toward a more general model of intellectual diffusion, we believe it is important to characterize the social structure of the American legal professoriate. Its *self-organization*[4] offers one possible causal mechanism for the emergence of and convergence upon conceptions of what constitutes a sound legal rule. Thus, we explore the architecture of the legal academy, the relative authority of particular institutions, and prospects for diffusion across its component institutions.

While many empirical approaches might be applied to the development and spread of intellectual and doctrinal paradigms, one particularly useful manner of representing the interactions between various entities across such a

1. Brandwein identifies the case method as significant for locking in the dominant account of the Waite Court's state action jurisprudence. *See* Pamela Brandwein, A Judicial Abandonment of Blacks? Rethinking the "State Action" Cases of the Waite Court, 41 Law & Soc'y Rev. 343, 374-375 (2007) ("So what did the case method mean for study of the Civil Rights Cases (1883)? It meant that the decision was slated for study, isolated from legal materials crucial for understanding the Waite Court's 'state action' jurisprudence. This isolation can be seen in the very first constitutional law casebook, the two-volume cases on Constitutional Law (1895) by Thayer. ...Thayer's casebook thus exemplifies the practice of isolating the study of the Civil Rights cases."). Mark Graber, Transforming Free Speech: The Ambiguous Legacy of Civil Libertarianism (Univ. of California Press 1991). In describing the development of modern First Amendment theory, Graber highlights the pivotal role played by Harvard Law Professor Zechariah Chafee.

2. In addition to these important works, additional historical institutionalist scholarship exists analyzing other important constitutional narratives. For example, consider the analysis of the Supreme Court's decision in Lochner v. New York, 198 U.S. 45 (1905). *See* Howard Gillman, The Constitution Besieged: The Rise and Demise of Lochner Era Police Powers Jurisprudence (Duke 1992), as well as the examination of New Deal "Switch in Time," Barry Cushman, Rethinking the New Deal Court: The Structure of a Constitutional Revolution (Oxford 1998). Evaluating the record, these historical institutionalist scholars place long-standing and dominant accounts under significant stress.

3. *See* Pamela Brandwein, Reconstructing Reconstruction: The Supreme Court and the Production of Historical Truth (Duke 1999).

4. Self-organization is a term of art commonly used to describe the collective behavior of a variety of social and physical systems. While there exist slightly varying definitions, the term is often used to describe a system whose behavior becomes increasingly organized without being directly managed by an outside source. Examples of self-organization can be seen in physical science fields such as chemistry (molecular self-assembly), physics (spontaneous magnetization), and biology (homeostasis). Such ideas have also been invoked in the social sciences to describe flocking behavior (sociology) and the behavior of markets (economics). For example, the often-quoted Austrian economist Friedrich Hayek described capitalism as a self-organizing system of voluntary cooperation. *See* Friedrich A. Hayek, The Use of Knowledge in Society, Am. Econ. Rev. Sept. 1945, at 519.

complex adaptive system[5] is network analysis. Drawing from available information on each tenure-track professor employed by an ABA accredited institution, Section II of this article applies and extends the framework used in Fowler, Grofman & Masuoka.[6] Our analysis reveals an extremely skewed distribution of social authority—even more than is present in other intellectual disciplines in the social sciences. As described herein, we believe this extreme skewing has a variety of consequences including the ranking of institutions as well as the broader development of American law.

As previously documented in literature, such a pattern does not arise through happenstance. Rather, a range of mathematically derived micro-level generating processes are plausibly responsible for producing various observed macro structures. This pattern characterizes not only substantive decisional outputs but also extends to self-organization of actors. Indeed, our findings are consistent with the work of a variety of scholars,[7] all of whom document the tendency of common law systems and their constitutive institutions to self-organize in a "fractal," "crystalline," "highly-skewed," and/or "scale-invariant" manner.[8]

As we believe the acceptance or rejection of particular paradigms is, at least in part, a function of the social spread of information, we draw from literature in social epidemiology, and in Section III we provide a first-order computational model for an information diffusion process. Our model provides a parsimonious display of the tradeoff between idea infectiousness and structural position within the network. The model demonstrates how, for historically elite institutions, their structural position allows such schools

5. A growing literature demonstrates that various components of American law display properties consistent with a complex system. *E.g.*, Daniel M. Katz & Derek K. Stafford, Hustle and Flow: A Social Network Analysis of the American Federal Judiciary, 71 Ohio St. L.J. 457 (2010); J.B. Ruhl, Law's Complexity: A Primer, 24 Ga. St. U. L. Rev. 885 (2008); Bernard Trujillo, Patterns in a Complex System: An Empirical Study of Valuation in Business Bankruptcy Cases, 53 UCLA L. Rev. 357 (2005); David G. Post & Michael B. Eisen, How Long is the Coastline of the Law? Thoughts on the Fractal Nature of Legal Systems, 29 J. Legal Stud. 545 (2000); J.B. Ruhl, The Fitness of Law: Using Complexity Theory to Describe the Evolution of Law and Society and Its Practical Meaning for Democracy, 49 Vand. L. Rev. 1407 (1996).

6. *See* James H. Fowler, Bernard N. Grofman & Natalie Masuoka, Social Networks in Political Science: Hiring and Placement of PhDs, 1960–2002, PS: Pol. Sci. & Pol., Oct. 2007, at 729.

7. *E.g.*, Thomas A. Smith, The Web of the Law, 44 San Diego L. Rev. 309 (2007); Elizabeth A. Leicht, et al., Large-Scale Structure of Time Evolving Citation Networks, 59 Eur. Physical J. B. 75 (2007); Daniel A. Farber, Earthquakes and Tremors in Statutory Interpretation: An Empirical Study of the Dynamics of Interpretation, 89 Minn. L. Rev. 848 (2005); Post & Eisen, *supra* note 5; Jack Balkin, The Promise of Legal Semiotics, 69 Tex. L. Rev. 1831, 1835-36 (1991).

8. For example, in their consideration of the structure of the American federal judiciary and an outline of one possible generating mechanism responsible for the extreme skewing of authority, see Katz & Stafford, *supra* note 5. These authors isolate some variant of the preferential attachment model first outlined in the physics literature; *see* Reka Albert & Albert-László Barabási, Emergence of Scaling in Random Networks, 286 Science 509 (1999).

to become intellectual super-spreaders. While our model is fairly simple, we hope our foray into computational legal studies[9] will, at a minimum, motivate future scholarship.

1. Data Collection

In order to generate an empirically grounded picture of the social topology of the American legal academy, we collected available information on the tenured or tenure-track faculty of each institution accredited by the American Bar Association (ABA) and listed in the *U.S. News & World Report* rankings. While the Association of American Law Schools (AALS) produces a directory of faculty members employed at various institutions, we decided to vet this information by independently collecting data on each institution's core faculty. This direct collection effort was undertaken during the early spring of 2008.[10] Although time-consuming, this process proved fruitful, as virtually every institution maintains a detailed online listing of its faculty. Therefore, using publicly available web pages, it was possible on the first cut to obtain relevant information on virtually every tenured or tenure-track professor.[11] In the rare instance that we could not ascertain the exact employment status of a listed faculty member, we relied on secondary sources to determine whether to include a particular individual. Such adjudicating information included the professor's exact title, nature of their scholarship, and the content of their recently taught courses.[12] Each line of the dataset was independently vetted by at least two coders.

9. Computational legal studies is a sub-field dedicated to applying tools from computer science, applied physics, informatics, complex systems and applied mathematics to help enrich positive legal theory. *See* http://computationallegalstudies.com/. The approaches highlighted herein are but a small slice of the wider set of available methods. Such tools include agent based modeling, network analysis, machine learning, evolutionary computation, natural language processing, and data mining. While the approaches have analogs to traditional techniques, there are important distinctions between commonly used analytical methods and a computational legal studies approach. For recent relevant work outlining the new age of "computational social science," see David Lazer, et al., Computational Social Science, 323 Science 721 (2009). A special themed issue of Science Magazine entitled "Complex Systems & Networks" was recently devoted to methods relevant to the field. *See, e.g.*, Adrian Cho, Ourselves and Our Interactions, 325 Science 406 (2009); Albert-László Barabási, Scale-Free Networks: A Decade and Beyond, 325 Science 412 (2009); Carter Butts, Revisiting Foundations of Network Analysis, 325 Science 414 (2009); Elinor Ostrom, A General Framework for Analyzing Sustainability of Social-Ecological Systems, 325 Science 419 (2009); Alessandro Vespignani, Predicting the Behavior of Techno-Social Systems, 325 Science 425 (2009).

10. We selected this mid-year period for the information acquisition as it was least likely to overlap with faculty turnover.

11. We excluded from our analysis all non-tenure track professors including legal writing, clinical professors, lecturers, and adjunct instructors.

12. In a very limited number of instances, it was necessary to rely upon external sources such as Martindale-Hubbell. We cross-referenced that information using a variety of web based querying techniques.

Appendix I *infra* contains a selected sample of our data set. As Appendix I illustrates, the broader data includes specific information on the academic institution where the individual earned his or her first American law degree. Our data also includes a significant and growing population of individuals who possess no American law degree. These individuals fall primarily into two categories: those who exclusively possess legal training from a non-U.S. institution,[13] or individuals who obtained a Ph.D. in an academic field but did not earn a U.S. law degree.[14] While we included these individuals in the dataset, we excluded from our analysis all individuals who did not possess some form of American law degree (J.D., L.L.B., L.L.M., or S.J.D.). Consistent with our broader strategy, joint J.D./Ph.D.'s were indexed using the institution that granted their primary law degree. Particularly among historically elite institutions, the data contained a large number of self-loops (i.e., individuals employed at the same institution they formerly attended).[15] We followed the approach of Fowler, Grofman & Masuoka who explicitly decided against the inclusion of self-loops in the study of political science hiring and placement.[16] In sum, our process yielded a significant dataset containing information on the more than 7,200 legal academics and 184 institutions that together comprise the American legal academy.

With the information acquired, we sought to analyze the patterns contained therein. Despite being largely decentralized—with decisions being rendered independently at each respective institution—we suspected a broad pattern would emerge. Indeed, given the prior evidence[17] we suspected the academy would self-organize in a relatively hierarchical manner. However, the extent of this self-organized hierarchy was one of the questions we sought to answer.

13. The majority of such institutions where located in the United Kingdom, Canada or Australia.

14. A function of the rise of both the law and economics and empirical legal studies movements, a majority of such individuals held a Ph.D. in either Political Science or Economics.

15. Loops are located in the diagonal of the adjacency matrix $A: = a_{ij} : m{\times}n$ where a loop occurs when $i = j$. For relevant work on such self-loops see Ted Eisenberg & Martin Wells, Inbreeding in Law School Hiring: Assessing the Performance of Faculty Hired from Within, 29 J. of Leg. Stud. 369 (2000).

16. Fowler, Grofman & Masuoka, *supra* note 6. Given the small number of self-loops present in political science, their exclusion from the prior study was entirely sensible. Although there are certainly more self-loops in law professor hiring and placement, we still believe their exclusion is appropriate as many of the loops are concentrated at historically elite institutions. Thus, if anything, their omission should downwardly weight the authority of these law schools, yielding conservative estimates of the concentration of authority as well as the relative strength of such key institutions.

17. *E.g.*, Richard E. Redding, "Where Did You Go to Law School?" Gatekeeping for the Professoriate and its Implications for Legal Education, 53 J. Legal Educ. 594 (2003); Robert J. Borthwick & Jordan R. Schau, Gatekeepers of the Profession: An Empirical Profile of the Nation's Law Professors, 25 Mich. J. L. Reform 191 (1991); Jerome A. Barron & Elyce H. Zenoff, So You Want to Hire a Law Professor? 33 J. Legal Educ. 492 (1983).

II. A Network Representation of Hiring and Placement Within the American Law Professoriate

While traditionally the province of mathematical sociology, the study of networks has recently been performed by scholars across the physical and social sciences. Indeed, network science is a genuinely interdisciplinary field as it draws scholars from wide ranging disciplines including physics, political science, applied mathematics, biology, computer science and economics. While certainly not yet part of the mainstream legal literature, there have been a series of recent articles applying elements of network science to various substantive domains including patents,[18] telecommunications regulation,[19] judicial decision-making,[20] and the structure of the law.[21] Using the data described above and leveraging analytical techniques from the broader network science literature, we sought to first map the internal social structure of the American legal academy, and second consider implications of that structure for the development of the law.

Networks generally consist of two primary components—*nodes* and *edges*. In social science applications, nodes typically represent actors or institutions, while edges represent connections between such entities. Edges can be either directed, to represent connections that flow from one node to another, or undirected. They can simply signify the existence of a connection, taking on a discrete value of 0 or 1, or they can be weighted to reflect the strength of the connection between two nodes. Edges can represent a wide class of potential connections including social ties, the flow of goods between firms or countries, and the linkages between various actors or institutions.

Given a reasonably well-specified network topology, it is possible to develop a model of diffusion for a particular pathogen. For example, networks are often used as the architecture in social epidemiology models, where the relevant pathogen could be a virus such as the swine flu or the norovirus. Using a similar approach, it is also possible to consider the spread of particular ideas or social norms within a given system where most ideas or norms do not succeed but a few persist and become reasonably well accepted.

A precursor to considering the spread of ideas and norms is the characterization of the relevant network architecture. Thus, in a manner

18. *See* Katherine J. Strandburg, Gabor Csardi, Jan Tobochnik, Peter Erdi & Laszlo Zalanyi, Patent Citation Networks Revisited: Signs of a Twenty-First Century Change?, 87 N. C. L. Rev. 1657 (2009); Katherine J. Strandburg, Gabor Csardi, Jan Tobochnik, Peter Erdi & Laszlo Zalanyi, Law and the Science of Networks: An Overview and an Application to the "Patent Explosion," 21 Berkeley Tech. L. J. 1293 (2007).

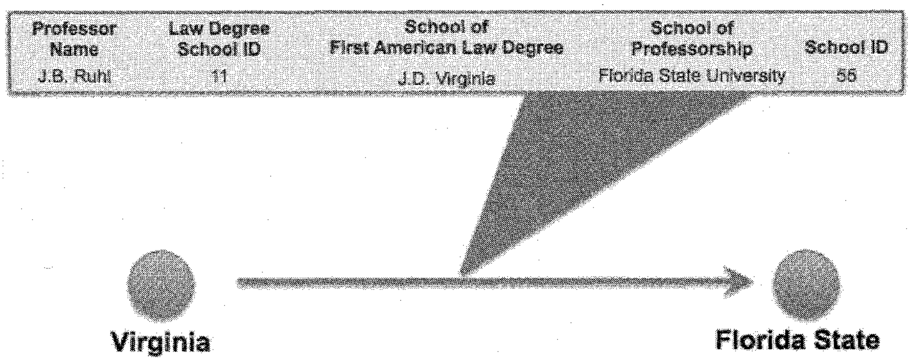
19. Daniel F. Spulber & Christopher S. Yoo, On the Regulation of Networks as Complex Systems: A Graph Theory Approach, 99 Nw. U. L. Rev. 1687 (2005).

20. Katz & Stafford, *supra* note 8; Daniel Katz, Derek Stafford & Eric Provins, Social Architecture, Judicial Peer Effects and the 'Evolution' of the Law: Toward a Positive Theory of Judicial Social Structure, 23 Ga. St. U. L. Rev. 975 (2008).

21. Michael James Bommarito II, et al., Distance Measures for Dynamic Citation Networks, 389 Physica A 4201 (2010); Smith, *supra* note 7.

consistent with the approach undertaken by Fowler, Grofman & Masuoka,[22] we transformed our dataset into a set of directed dyadic relations between the institution where a given individual received their initial socialization and the institution where that individual now acts to socialize the next generation.[23] Figure 1 offers a discrete example of the transition from the dataset to a graph theoretic representation.

Figure 1. From a Data Set to a Graph-Theoretic Representation



While Figure 1 offers a clear representation of individual entry, it is virtually impossible to manually visualize the type of large-scale dataset we consider herein. However, recent developments in computer science, physics and mathematical sociology allow for the algorithmic visualization of networks of significant size. We used a spring-embedded, force-directed placement algorithm[24] commonly used by scholars to visualize networks roughly the size of the American law professoriate. This automated placement algorithm is useful because it typically produces graphs with attractive properties such as minimized edge crossings, efficient use of the planar area, and minimized difference in edge lengths. Applying the Kamada-Kawai approach, Figure 2 offers a representation of the full-directed network of hiring and placement.

Figure 2 conveys a significant amount of information in a single visualization. Each institution is sized by total number of placements. Thus, the nodes representing top placing institutions such as Harvard are large while institutions such as Ave Maria are quite small. Additionally, the location of the nodes in the graph is a function of the "quality" of its respective placements. Schools with higher quality placements are closer to the center of the network while schools that are closer to the boundary feature less prominent placements.

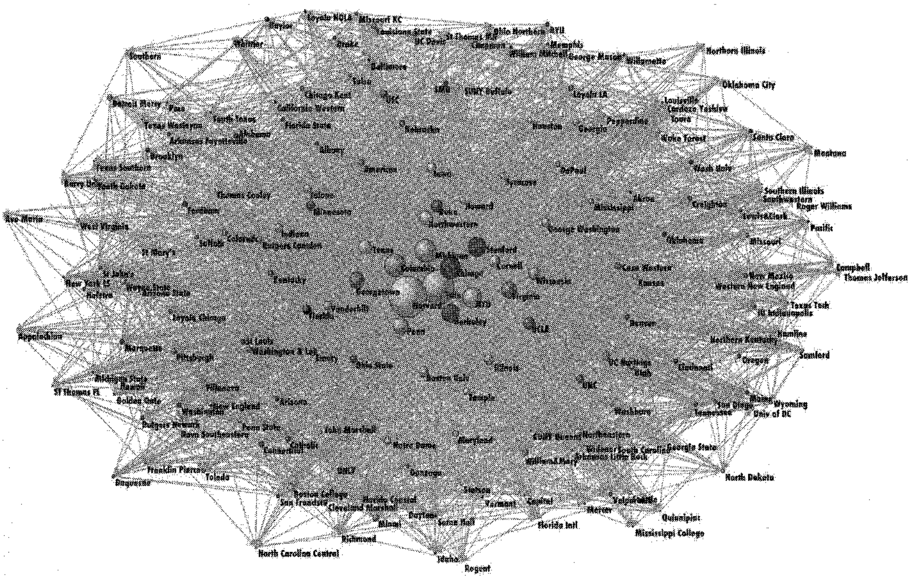
22. Fowler, Grofman & Masuoka, *supra* note 6.

23. In graph-theoretic terms, we used a weighted and directed unipartite graph.

24. This was developed by Eades and further by Kamada & Kawai (1989). *See* Peter Eades, A Heuristic for Graph Drawing, 42 Congressus Numerantium 149 (1984); Tomishia Kamada & Satoru Kawai, An Algorithm for Drawing General Undirected Graphs, 31 Info. Processing Letters 7 (1989).

In their mapping of the hiring and placement of political science Ph.D.'s, Fowler, Grofman & Masuoka note "our graphical representations clearly show the structure of the discipline in terms of what might be conceived of as a core-periphery network."[25] Figure 2 shows an analogous structure for the American legal academy, as a fairly small core of elite law schools distinguish themselves with their positions of high structural importance within the broader network. Indeed, broadly considered, Figure 2 displays a fairly dense set of core institutions occupying a highly central network position.

Figure 2. The Hiring and Placement Network for the American Law Professoriate[26]



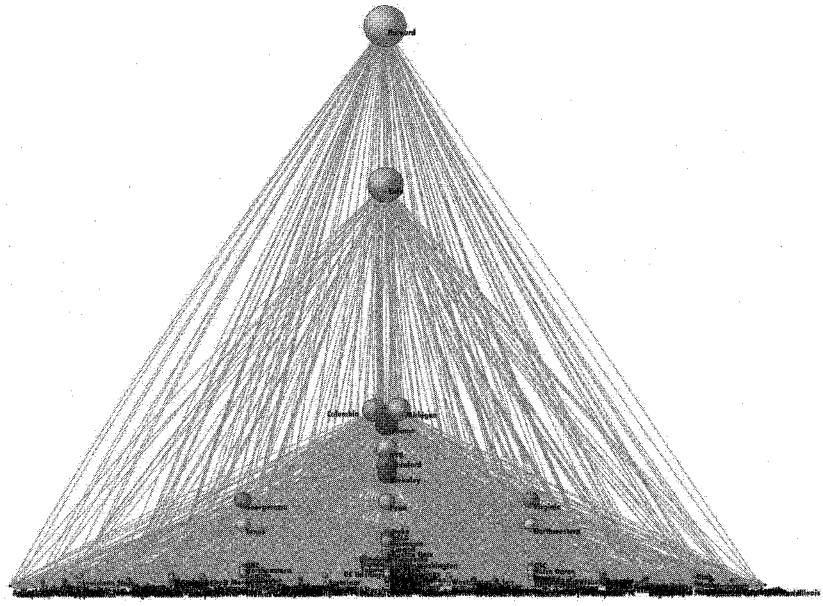
Through an alternative representation, Figure 3 demonstrates the dominance of an isolated number of institutions. This visualization yields a hierarchical depiction of the network–a representation that helps uncover latent distribution of authority contained therein. While Figure 3 bunches a large number of institutions into its base, it is important to note this crowding is data-driven. Namely, it yields a visualization of the data that does justice to the relative distances between institutions. Consistent with

25. *See supra* note 6; *see also* Stephen Borgatti & M.G. Everett, Models of Core/Periphery Structures, Soc. Networks, 1999, at 375; Michael G. Bisciglia, Scott L. Feld & Marcus Ynalvez, Why Your Department Has Placed Fewer Students Than The One That Trained You: Principles of Directed Mobility as a Consequence of In-Out Variation (La. St. U. Dep't. Soc., Working Paper, 2003).

26. To view a high quality color rendering of this image and other related supplementary materials, please visit http://computationallegalstudies.com/jle-law-prof-article/.

the degree distribution discussed below as well as prior scholarship,[27] Figure 3 provides some visual indication of an important difference between hiring and placement in political science with hiring and placement within the legal academy. Namely, unlike departments of political science,[28] the aggregation of all individual-level decisions by law hiring committees converges not upon a cluster of institutions but rather upon two institutions–Harvard and Yale.[29]

Figure 3. A Hierarchical View of the Hiring & Placement Network[30]



III. The Network Structure of the American Law Professoriate: Node Level Centrality Measures

While the automated graph visualization techniques used to generate Figure 2 and Figure 3 are useful for observing the relative placement of institutions as well as the broad compositional properties of a given network, the literature recognizes that these approaches are only heuristic representations of the

27. *E.g.*, Redding, *supra* note 17.

28. Fowler, Grofman & Masuoka, *supra* note 6.

29. As our interest is in simply the raw number of placements, we do not control for institutional size. Thus, the visualization in Figure 3 undoubtedly favors an institution such Harvard whose class size far exceeds that of Yale.

30. To view a high quality color rendering of this image and other related supplementary materials please visit http://computationallegalstudies.com/jle-law-prof-article/.

underlying structure.[31] To best characterize a given network, scholars apply statistical techniques developed in the network science literature, as these metrics offer transparent and replicable depictions of the underlying data.

Prior studies of the American law professoriate, including Leiter,[32] employ an individual level approach seeking to consider the "best law schools for the 'best' jobs in law teaching." This individual level approach is typically considered through the eyes of an applicant asking in probabilistic terms, "which institution gives *me* the best chance to secure a top level law teaching job?" Considering this question, scholars such Leiter typically control for characteristics such as institutional size. One potential shortcoming of this approach surrounds questions of functional form. Namely, it is not clear that placements linearly scale to differences in the size of graduating classes. In other words, it is not clear that simply dividing placements by number of yearly graduates per school represents the appropriate specification.

Bracketing the specification problem, if the question were restructured to consider hiring and placement at the institutional level, all else equal, size is simply a factor endowment where the sheer volume of graduates produced by certain institutions may allow ideas generated at those institutions to outperform the ideas generated at their smaller counterparts. With this caveat in Tables 1-3, we offer three traditional node level centrality measures useful for determining the relative standing of various institutions: OutDegree, Hub Score and Closeness.[33] Each measure employs a different criterion to assess the relative strength of each individual law school. Tables 1-3 below display these differential rankings.

As the existing network is an artifact of votes over the applicants minted from various institutions at various time periods, there is likely some rough mapping to faculty quality in these aggregate decisions. Yet, it is important to remember that our analysis omits consideration of other factors relevant to a comprehensive analysis including various bibliometric measures of intellectual prowess. Indeed, faculty quality is a question with multiple dimensions

31. Specifically, the Kamada-Kawai Layout employs a heuristic approach to placement where only a single vertex is seated at a given time. A given vertex is chosen to be the "most promising" vertex with the maximum gradient value of

$$\Delta_m = \sqrt{\left(\frac{\partial E}{\partial x_m}\right)^2 + \left(\frac{\partial E}{\partial y_m}\right)^2}$$

Once the vertex to be moved (m) is chosen all other vertices are fixed and the energy is (locally) minimized by only moving vertex m. This is done using a single-sided, two-dimensional Newton-Raphson iteration. To find the root of a function f (x) in one dimension, Newton-Raphson iterates

$$X_{t+1} \leftarrow X_t - \frac{f(x_t)}{f'(x_t)}$$

32. Brian Leiter, Brian Leiter's Best Law Schools for the "Best" Jobs in Law Teaching, May 25, 2006, *available at* http://www.leiterrankings.com/jobs/2006job_teaching.shtml.

33. *See* Fowler, Grofman & Masuoka, *supra* note 6. For reasons cited, we do not calculate either eigenvector centrality or one of the many variations of Google's "Page Rank" Algorithm.

including but not limited to quality of academic training, quality of intellect, work ethic, intellectual curiosity as well as a wide number of other individual, structural, and stochastic factors.

Our analysis is an initial attempt to measure the structural position of various institutions because all else equal, the patterns displayed in such a network offer an initial indication of one class of intellectual diffusion that could be plausibly anticipated. While there certainly exist other social and professional networks of legal elites capable of supporting the diffusion of ideas, we believe this article represents a worthwhile contribution to a broader model of intellectual diffusion within American law. Thus, the analysis presented herein should be considered the beginning and not the end of such a discussion.

A. Calculating OutDegree

With all of its well-documented faults,[34] *U.S. News* purports to provide a composite picture for an institution—one where faculty quality at best represents only a component of broader inquiry.[35] While imperfect in some respects, we believe our measure compares favorably to the qualitative survey used to generate the *U.S. News* peer assessment. Namely, surveys seek to capture opinion, but given that talk is cheap, it is unclear whether the preferences stated in a survey actually map to observed behavior. In this respect, our measure is useful because it represents aggregate revealed preferences over institutions and is generated in a context where a significant commitment of financial resources hangs in the balance.

Each placement from one law school to another constitutes a direct and directed connection between the schools.[36] In a directed network, the outdegree is the tally of all connections emanating from a given institution. When we remove loops from the network (i.e. cases where a professor teaches at the same institution where he or she received training), Harvard Law School has outdegree = 993 while nine law schools have outdegree = 0. In that vein, although blunt in some respects, outdegree provides a glimpse into the relative standing of each institution.

34. *See* Jeffrey Stake, The Interplay Between Law School Rankings, Reputations, and Resource Allocation: Ways Rankings Mislead, 89 Ind. L. J. 229 (2006). As an example of the wider critical literature, the author offers perhaps the most stinging indictment of the U.S. News Rankings.

35. For a useful description of the U.S. News Rankings, see Theodore P. Seto, Understanding the U.S. News Law School Rankings, 60 SMU L. Rev. 493 (2007).

36. The outdegree of a node ni is a count of the number of arcs (directed connections) emanating from ni. Formally, Wasserman & Faust define outdegree, do (ni), as the "number of arcs of the form $l_k = \langle n_i, n_j \rangle$ for all $l_k \in L$ and all $n_j \in N$" (126). *See* Stanley Wasserman & Katherine Faust, Social Network Analysis: Methods and Applications (Cambridge 1994).

In Table 1 below, we display the Top 50 institutions as measured by outdegree. For purposes of comparison, we include a rank of each institution using its "peer assessment" score.[37] While generally similar for many institutions, our approach provides non-trivial differences from *U.S. News* for several institutions. For example, as Table 1 indicates institutions such as Syracuse, Wayne State, Howard, and Northeastern University Law School far outperform their *U.S. News* peer assessment.

As a measure of potential structural influence, however, outdegree has a serious drawback: It provides all connections incident to each vertex equal weight. As such, it does not differentiate a link between Harvard and Ave Maria from a link between Harvard and Michigan. Thus, outdegree does not account for the varying prestige levels of the nodes from which the connections originate or for the prestige of the nodes in which connections terminate. The well-known Kleinberg's "Hubs and Authorities" algorithm, an approach similar to Google's PageRank™, represents an attempt to remedy this problem.

B. Calculating Hubs and Authorities

Kleinberg[38] has noted the above problem with count measures such as outdegree. Namely, standard degree measures do not account for the social standing of nodes to which arcs connect. To remedy this shortcoming, Kleinberg defines two types of nodes, "hubs" and "authorities." Hubs are nodes with many placements to other high prestige nodes. Authorities are nodes that receive (or hire) from high prestige nodes. Designed to consider dispersal of influence within the world-wide-web, the "hub and authority" value the Kleinberg algorithm assigns is a function of the social prestige of its neighbors. As noted by Fowler, Grofman & Masuoka,[39] a "good hub points to many good authorities, and a good authority is pointed to by many good hubs." In other words, hubs are the schools with a high degree of influence on *other* influential schools within the network. Therefore, this measure better represents the relative influence of various nodes within a network.[40]

Given the specific nature of the institutions in question, we are interested primarily in recording Kleinberg's "hub" values for each node in our network. Authority scores are not reported in this article because their substantive meaning is not useful for purposes of this social inquiry. While certain

37. Using solely the "peer assessment," we assigned each institution a rank based upon their relative performance. This includes assigning ranks to institutions located in the third and fourth tier. If two or more institutions were tied, we assigned each institution the highest possible rank.

38. *See* Jon Kleinberg, Authoritative Sources in a Hyperlinked Environment, 46 J. Ass'n Computing Machinery 668 (1999).

39. *See* Fowler, Grofman & Masuoka, *supra* note 6.

40. We implemented the Kleinberg algorithm in the statistical program R using the igraph package. For access to the igraph package see The Igraph Library, *available at* http://igraph.sourceforge.net/.

institutions display local variation, Table 2 illustrates how the consideration of placement quality does not dramatically alter the qualitative results.

Like all measures of influence and social structure, however, Kleinberg's measure has its limitations. By placing additional weight on the ties between influential nodes within a network, "hubs and authorities" values do not account for the potential impact of a node that has neither high hiring nor placement capacity, but has otherwise hired from central nodes. Our final measure of influence attempts to capture this important dimension.

C. Calculating Closeness

The last influence measure we calculate is closeness.[41] The closeness score of a given institution is simply a calculation of the shortest paths from that node to all other nodes in the network. This calculation is usually normalized so the score lies on a common spectrum between 0 and 1.[42]

Unlike the previous two measures, closeness directly accounts for a node's position in the network. According to our measure, closeness centrality is greater for nodes that are more important to the structure of the network, having shorter network distances to other nodes on average. As a measure of social centrality, closeness is not without it own limitations. Namely, it is theoretically possible for an institution to feature few connections (out degree) and relatively low individual prestige (hubs), but still display a relatively high closeness score. In particular, if the institution possesses a particular set of placements, relative to the balance of the graph, its closeness score will far outstrip its scoring under alternative measures. This differential is still substantively valuable for diffusion as the spread of information throughout the network may very well be accelerated by passing through such an institution.[43] However, we believe closeness, like its counterpart measures of centrality, should not form the unilateral basis for characterizing a given node.

41. Closeness relies upon the calculation of geodesic paths. A geodesic path, dG , is the shortest path between two nodes within a network—with travel between nodes limited to the arcs (or edges) that comprise the network. Formally, it is calculated as follows: $$C_c(n_i) = \frac{N-1}{\sum_{n_j \in N}^{N} d_G(n_i, n_j)}$$

42. The calculation we employ here is the normalized reciprocal of the formula provided in Wasserman and Faust. *See* Wasserman & Faust, *supra* note 36. We employ this measure for two reasons: 1) the normalized nature of the measure allows for easier comparison of closeness scores across networks, and 2) the reciprocal has now become the most common formula.

43. In calculating closeness, we do not weight the arcs between nodes as we are concerned the weighting of the arcs based on our pre-conceived idea of network structure would bias our results.

Table 1. Top Fifty Institutions Ranked By Out Degree

Out Degree Rank	*U.S. News* Peer Assessment Score (2008)	Raw Out Degree	Institution
1	1	993	Harvard
2	1	712	Yale
3	5	309	Michigan
4	4	308	Columbia
5	5	288	Chicago
6	8	245	NYU
7	1	217	Stanford
8	8	201	Berkeley
9	5	154	Virginia
10	10	154	Georgetown
11	10	152	Penn
12	14	111	Northwestern
13	15	111	Texas
14	10	91	Duke
15	19	87	UCLA
16	10	83	Cornell
17	28	82	Wisconsin
18	28	67	Boston University
19	24	59	Illinois
20	28	57	Minnesota
21	24	55	Iowa
22	41	53	Florida
23	19	50	George Washington
24	16	45	Vanderbilt
25	34	43	Tulane
26	28	42	Indiana
27	24	38	UC Hastings
28	24	36	Boston College
29	28	35	USC
30	19	35	UNC
31	35	34	Ohio State
32	19	32	Notre Dame
33	82	32	Northeastern

34	56	30	Case Western
35	19	29	Emory
36	56	29	Temple
37	72	28	Miami
38	106	26	Howard
39	72	26	Syracuse
40	82	25	Rutgers-Camden
41	106	24	Wayne State
42	41	23	Georgia
43	47	23	Maryland
44	56	23	Kansas
45	28	22	William & Mary
46	64	22	Kentucky
47	17	21	Washington & Lee
48	47	21	American
49	72	21	Pittsburgh
50	64	21	Utah

Table 2. Top Fifty Institutions Ranked by Hub Score

Hub Score Rank	*U.S. News* Peer Assessment Score (2008)	Hub Score	Institution
1	1	1.0000000	Harvard
2	1	0.9048631	Yale
3	5	0.8511497	Michigan
4	4	0.7952253	Columbia
5	5	0.7737389	Chicago
6	8	0.7026757	NYU
7	1	0.6668868	Stanford
8	8	0.6607399	Berkeley
9	10	0.6457157	Penn
10	10	0.6255498	Georgetown
11	5	0.5854464	Virginia
12	14	0.5014904	Northwestern
13	10	0.4138745	Duke
14	10	0.4075353	Cornell
15	15	0.3977734	Texas

16	28	0.3787268	Wisconsin
17	19	0.3273598	UCLA
18	24	0.2959581	Illinois
19	28	0.2919847	Boston University
20	28	0.2513371	Minnesota
21	24	0.2403289	Iowa
22	28	0.2275534	Indiana
23	19	0.2235015	George Washington
24	16	0.2174677	Vanderbilt
25	41	0.2012442	Florida
26	24	0.1999686	UC Hastings
27	34	0.1974877	Tulane
28	28	0.1749897	USC
29	35	0.1702638	Ohio State
30	24	0.1586516	Boston College
31	72	0.1543831	Syracuse
32	19	0.1537236	UNC
33	56	0.1525355	Case Western
34	82	0.1511569	Northeastern
35	19	0.1428239	Notre Dame
36	56	0.1286375	Temple
37	82	0.1232289	Rutgers Camden
38	56	0.1227421	Kansas
39	64	0.1213358	Connecticut
40	47	0.1198901	American
41	34	0.1162101	Fordham
42	64	0.1150860	Kentucky
43	106	0.1148082	Howard
44	47	0.1125957	Maryland
45	28	0.1101975	William & Mary
46	56	0.1058079	Colorado
47	19	0.1041129	Emory
48	17	0.1031490	Washington & Lee
49	72	0.1027442	Miami
50	103	0.1006172	SUNY Buffalo

Table 3. Top Fifty Institutions Ranked by Closeness Score

Closeness Rank	*U.S.News* Peer Assessment Score (2008)	Closeness Score	Institution
1	1	0.910447	Harvard
2	1	0.835614	Yale
3	5	0.806167	Michigan
4	5	0.759336	Chicago
5	4	0.759336	Columbia
6	8	0.726190	NYU
7	1	0.698473	Stanford
8	8	0.698473	Berkeley
9	10	0.693181	Georgetown
10	10	0.687969	Penn
11	5	0.670329	Virginia
12	14	0.635416	Northwestern
13	10	0.61	Duke
14	15	0.61	Texas
15	10	0.6	Cornell
16	28	0.6	Wisconsin
17	19	0.580952	UCLA
18	24	0.571875	Illinois
19	28	0.564814	Minnesota
20	28	0.563076	Boston University
21	19	0.556231	George Washington
22	34	0.551204	Tulane
23	24	0.547904	Iowa
24	28	0.547904	Indiana
25	28	0.536656	USC
26	82	0.527377	Rutgers Camden
27	35	0.524355	Ohio State
28	24	0.516949	UC Hastings
29	106	0.514044	Howard
30	56	0.511173	Case Western
31	28	0.509749	William & Mary
32	16	0.505524	Vanderbilt
33	41	0.501369	Florida

34	19	0.501369	UNC
35	64	0.497282	Connecticut
36	72	0.484127	Syracuse
37	64	0.480315	Nebraska
38	47	0.480315	Missouri
39	34	0.479057	Washington
40	72	0.476562	Cardozo Yeshiva
41	72	0.474093	Miami
42	56	0.472868	Kansas
43	47	0.471649	Maryland
44	24	0.470437	Boston College
45	82	0.464467	Cincinnati
46	56	0.463291	Temple
47	72	0.4575	Loyola LA
48	72	0.4563591	Catholic
49	56	0.4563591	Colorado
50	19	0.4507389	Notre Dame

IV. The Network Structure of the American Law Professoriate: Broad Structural Properties

Beyond providing characterizations at the node level, we consider the manner in which global social authority is distributed to provide potential insight into the nature of self-organization embraced by the broader social system. Specifically, it is important to remember that a given social structure need not assume any particular form. Instead, the aggregate topology of the network is a function of both the micro-level interactions between agents and the feedback processes that flow over the entire network. Despite the wide range of theoretical possibilities, such micro-interactions often follow patterns that are traceable to a discrete set of generative processes.

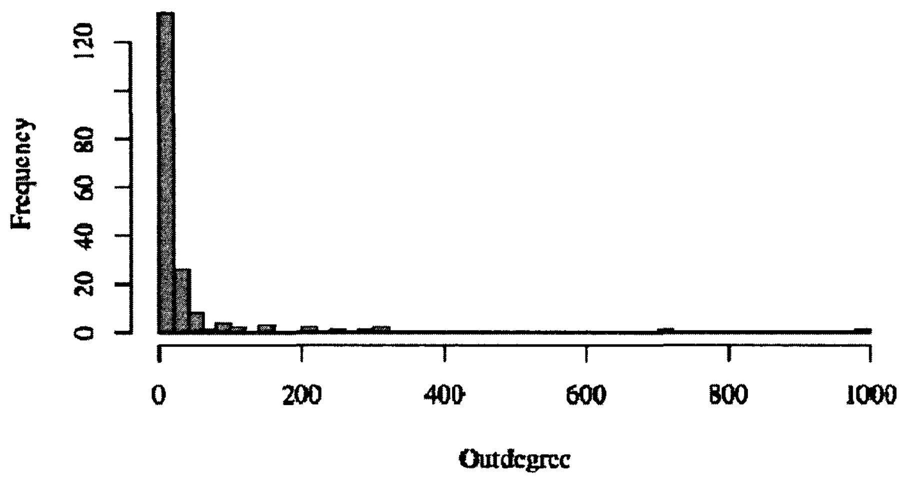
In allied work considering the self-organization of federal judges,[44] Katz, Stafford, and Provins offer a summary of some common network structures—including their degree distributions and likely micro-level generating mechanisms. Drawing from the network science literature, the authors describe four classic dependence graphs: Random, Clustered, Small World, and Scale-Free. Given that it can be difficult to adjudicate between these potential "states of the world," the extant literature has developed methods to characterize an observed network. Since each of these graphs is associated with a particular

44. *See* Katz, Stafford & Provins, *supra* note 20.

distribution of authority, the most common approach is to determine the number of connections held by each node and then plot distribution of those "degrees" across all nodes.

Taken together, scholars have offered empirical evidence supporting broad hypotheses about the highly skewed and/or fractal properties of legal systems.[45] Relying upon this earlier scholarship, we suspected the distribution of authority present in hiring and placement would likely mimic the previously documented pattern of extreme skewing.[46] To test this hypothesis, we plotted the distribution of authority for the institutions that together constitute the American legal academy. Figure 4 is a frequency distribution plot of the law schools by outdegree–where the outdegree is a count of the arcs incident to each node. From this plot, the classic the L-shaped curve consistent with extreme skewing emerges.

Figure 4. The Degree Distribution for the American Law Professoriate



In a large number of social and physical networks, including the mapping of authority within the American legal academy, the distribution of outdegrees is concentrated over a small subset of actors. While this "highly-skewed" distribution of degrees is most commonly associated with the power law distribution, a wide array of other closely linked distributions including the exponential, the power law with cutoff and log-linear distribution have a similar appearance.[47] One way to distinguish between these potential alternatives is

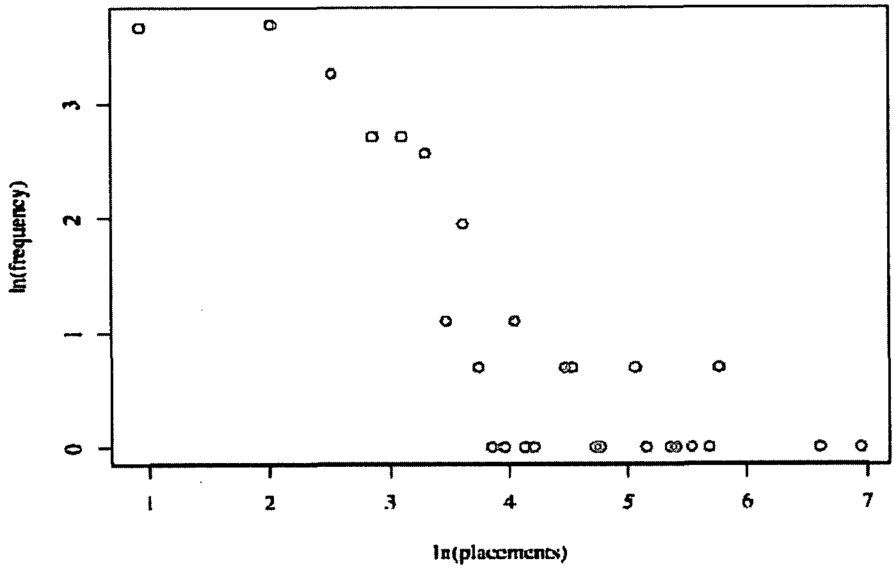
45. *E.g.*, Post & Eisen, *supra* note 5; Smith, *supra* note 7; Katz & Stafford, *supra* note 8.

46. One important class of skewed distributions, power law distributions, has been quite well documented in the applied math and physics literature. Such distributions display a very particular form of negative linear relationship.

47. Aaron Clauset, M.E.J. Newman & Cosma R. Shalizi, Power-Laws Distributions in Empirical Data, 51 SIAM Review 661 (2009) (offering a detailed description of these various distributions).

to plot the degree distribution on a log-log plot and measure its slope. Thus, in Figure 5, we generated a histogram of the degree frequencies and then took the log of the x and y-axis. This representation offers a log-log plot where the tail is fairly noisy.[48]

Figure 5. The Log-Log of the Degree Distribution for the American Law Professoriate



While characterizing the outdegree distribution may appear to be somewhat esoteric, there is a deeper substantive point at stake in the above analysis. One immediate implication of such an extremely skewed distribution is that use of serial ranks (i.e. 1, 2, 3) to describe the distances between institutions is likely to substantially obscure the actual distances between institutions. While ranks simply imply ordering, common experience indicates that end users tend to conflate them with linearized distance between units. Under some conditions, the use of a linear heuristic is not particularly problematic. However, this is not one of those cases. The plots displayed above taken together with the

48. It is important to note that given the relatively small size of the network, we cannot definitively characterize the distribution of authority. However, both Figure 4 and Figure 5 display a level of decline consistent with a highly-skewed degree distribution. Recent developments in the network science literature provide significant improvements on a mere visual assessment. For example, one technique uses maximum likelihood estimation (MLE) to allow for differentiation between the various flavors of highly skewed distributions. *See* M.E.J. Newman, Power Laws, Pareto Distributions and Zipf's Law, 46 Contemporary Physics 323 (2005). The use of this procedure is typically employed to determine whether a given plot is power law distributed. Using this approach, the alpha for the American law professoriate network is {-1.93}—just outside of the traditional $-2 < \alpha < -3$ power law range—but certainly consistent with the previous pattern of extreme skewing documented in studies such as Post & Eisen, *supra* note 5; Smith, *supra* note 7; and Katz & Stafford, *supra* note 8.

visualization shown in Figure 3 represent concrete evidence of the non-stationary distances that exist between certain sets of institutions. In other words, focusing exclusively on the question of law professor placement,[49] if one were to consider the actual distances rather than the ordinal distances between the institutions, their spacing features combinations of exponential and trivial gaps between institutions.

V. A Computational Model of Intellectual Diffusion Across the American Legal Academy

While the structure of the American legal academy defined herein is useful for identifying central actors as well as the relative distribution of authority, it is also serves as the foundation from which to consider the spread of information including doctrines and intellectual paradigms across its agents and institutions. Modeling the social spread of information is a difficult proposition as there exist many separate channels over which the relevant information pathogen might spread. While the diffusion of information from educational institution to student represents an important channel of information dissemination, even within a given institution not every student receives instruction from the same set of faculty. In addition, we believe legal socialization is only one of a broader set of possible diffusion mechanisms. For example, ideas are spread through many online platforms such as the SSRN, the legal blogosphere, as well as various email list servs. Additionally, conceptions of law are spread through various professional organizations including the Society for Empirical Legal Studies, American Society for Legal History, Society for Evolutionary Analysis in Law, American Law and Economics Association, as well as various components of the Association of American Law Schools.

Notwithstanding these limitations, we still believe the structure of the American law professoriate is directly relevant to the development of movements within law. Although we recognize computational models are still unfamiliar to most legal scholars, we introduce this modeling framework as we believe it might be usefully applied in the exploration of a variety of other theoretical questions. Under the umbrella of applied complexity theory, computational models have gained significant acceptance in fields such as evolutionary biology, physics, computer science, and engineering. While the social sciences have historically lagged, recent scholarship[50] offers reason to believe that generative social science is a modeling paradigm whose time has come.

49. It is important to note that unlike traditional academic departments such as political science, physics or anthropology the educational mission of a law school is not necessarily aimed at producing legal academics. Thus, institutions that rarely place a law professor may be highly successful in their mission of training students to be effective lawyers. The evidence presented herein only regards distances between institutions on the specific dimension in question.

50. *E.g.*, Joshua M. Epstein, Generative Social Science: Studies in Agent-Based Computational Modeling (Princeton 2007); John H. Miller & Scott E. Page, Complex Adaptive Systems: An Introduction to Computational Models of Social Life (Princeton 2007).

As many have observed,[51] the common law is a complex adaptive system in which an array of agents, institutions, and social contexts together act to produce its substantive jurisprudence. In the face of such complexity, it is tempting to assert that doctrinal transformations or the rise of intellectual paradigms are either entirely stochastic or the byproduct of some ill-defined set of social forces. In our estimation, the invocation of the "larger social forces" catchall has, for far too long, served as an end point for analysis. Developments in a wide variety of disciplines suggest an alternative. Specifically, while complex mechanisms are undoubtedly responsible for producing changes in the common law, this does not preclude a rigorous effort to understand the mechanics of such social processes using the best available analytical methods.

By embedding our empirical network into a computational model, it is possible to think concretely about how existing patterns of connections operate to increase or decrease the probability of reasonably wide spread acceptance. We choose a model of diffusion that weights parsimony over model complexity. Although our approach does not incorporate factors such as differential host susceptibility, countervailing information, and differential institutional "recovery" times, we believe it provides a useful first approximation of the dynamics of intellectual diffusion. Furthermore, given the static nature of our data set, we do not model network evolution or the type of social sorting considered by others.[52] We encourage future research designed to incorporate these important elements. In sum, while our approach represents a first cut, it does provide clean, tractable results and is consistent with the well-studied Reed-Frost model often used in epidemiology.[53]

We posit a mechanism of intellectual influence in which school B may be infected by an idea from another school A with probability, p, if an individual minted in A is hired as a faculty member for school B. This mechanism encompasses two distinct forms of potential influence. First, it models the impact of legal socialization. Legal socialization and the broader impacts of the law school experience have been considered by a variety of scholars.[54] In addition to the direct impact of legal education, our mechanism accounts for the role of former teachers as signal givers to their progeny. Namely, all else equal, and particularly prior to the receipt of tenure, we believe former students tend to contribute to the intellectual agenda outlined by their former

51. *See supra* note 5.

52. *E.g.*, Charles Tiebout, A Pure Theory of Local Expenditures, 64 J. Pol. Econ. 416 (1956); Ken Kollman, John H. Miller & Scott Page, Political Institutions and Sorting in a Tiebout Model, 87 Am. Econ. Rev. 977 (1997). By social sorting, we are contemplating the sort of intellectual homophily generated when individuals with similar intellectual commitments gravitate to the same institution.

53. For a classic examination of the Reed-Frost model, see H. Abbey, An Examination of the Reed-Frost Theory of Epidemics, 24 Hum. Biology 201 (1952).

54. *E.g.*, Duncan Kennedy, Legal Education and the Reproduction of Hierarchy: A Polemic Against the System (Afar 1983); and Elizabeth Mertz, The Language of Law School: Learning to "Think Like a Lawyer" (Oxford 2007).

professors, as conformity is easier than intellectual insurgency. Thus, if school A is a particularly successful at placing its students at many institutions (i.e., it features a strong hub score) this bodes well for the survival and diffusion of ideas starting at school A.[55]

We make the unrealistic assumption that all placed individuals are uniformly effective (and motivated) carriers of all ideas emanating from their "minting" institution. It is unclear whether this simplification has a strong influence on the explanatory and predictive power of the model with respect to the diffusion of actual ideas, but this question would be most appropriately treated in the context of an empirical case study, in which this type of model is used to explain the spread of an actual idea through the network.

As a general matter, our purpose in presenting the model is not to definitively characterize the spread of ideas among this class of legal elites. Indeed, a complete model of such phenomena would require far more detail and a significant amount of supporting empirical data. Instead, the purpose is to formalize the social spread of ideas, doctrines, and intellectual paradigms using a simple model of diffusion.

While our analysis models structural position and its role in accelerating or decelerating particular ideas, one open question is whether historically elite institutions are the generators of new approaches or simply the ratifiers of such ideas once offered. In other words, are historically elite institutions the real innovators? Are historically elite institutions engaging in "intellectual arbitrage" or are they using the previously developed market power to mimic the approaches undertaken by upstarts? Are Harvard and Yale more likely to be the initial generators of novel approaches to the understanding of law or are they simply institutions that act to accelerate the acceptance of these approaches once offered by actors at other institutions?

Casual observation indicates a somewhat mixed record. For example, consider several relatively recent intellectual movements within the legal academy including critical legal studies, law and society, evolutionary analysis and law, law as a complex system, empirical legal studies, and law and economics. While the members of the Harvard and Yale faculty were early adopters of some of these intellectual movements, it is clear that several of these paradigms trace their origins to institutions with a less central structural position. Initial generators of these successful intellectual movements come from institutions such as Chicago, Cornell, Florida State, George Mason, Indiana-Bloomington, Wisconsin, Washington University, and Vanderbilt.

55. In the interest of clarity and parsimony, our model does not account for the impact of institution B having many individuals from institution A, but simulations from a model with these features, not presented here, showed qualitatively similar results. This similarity makes intuitive sense, as the schools in our network which place individuals widely also, by and large, place the most individuals overall.

The Model

The graph G previously depicted in Figure 2 features nodes $n_i = \{n_1, n_2, \ldots n_{184}\}$ and directed edges $e_i = \{e_1, e_2, \ldots e_{7240}\}$. A directed graph such as G can be represented as a weighted adjacency matrix whereby a_{ij} represents a count of the number of edges from vertex i to vertex j. Alternatively, directed graph G can be represented as a binary adjacency matrix whereby $a_{ij} = 1$ if there exists any edge connecting node i to node j, and 0 otherwise. For the sake of parsimony, our model adopts the binary construction.[56]

The model is initially considered at $g = 0$, where g equals the current generation or time period. Using the binary adjacency matrix, our model releases idea d at $g = 0$. We classify adopters of idea d as active and non-adopters as inactive. For a single run of the model, idea d has a fixed infectiousness level, p, on the interval (0,1].[57] The infectiousness level p accounts for the intrinsic appeal of the idea to the broader population, where $p = 1$ when the idea infects every individual contacted with the particular idea.

Beginning with a selected n_i, the model processes the complete set of $n_{\neq i}$ by sweeping the n_i row of the adjacency matrix to determine the subset of nodes in the graph G directly reachable from n_i. With the previously fixed probability p, idea d is transmitted to the direct neighbors of n_i. Any neighbors reached by idea d are saved such that for each subsequent g, the process repeats and additional nodes are reached, until there remain no additional reachable nodes from any node n infected with idea d. In the given generation g where the process terminates, a count of total nodes reached by idea d is recorded.

The process described above was implemented in the programming language Python.[58] We repeatedly simulated the diffusion process for the 184 institutions contained in our network. In order to provide fairly robust estimates of the reach of the diffusion process, we ran five hundred separate diffusion trials at varying levels of p for each institution. Figure 6 contains the consensus diffusion plot for five representative institutions—Harvard, Washington University, South Carolina, Hamline and Southern Illinois.

In Figure 6, infectiousness p increases along the x axis as the number of schools reached by idea d increases along the y axis. The structural position of various institutions produces separation between institutions whose diffusion prospects are exponential, linear, and sub-linear. Namely, for some institutions, increases in the number of institutions reached by idea d scale linearly with

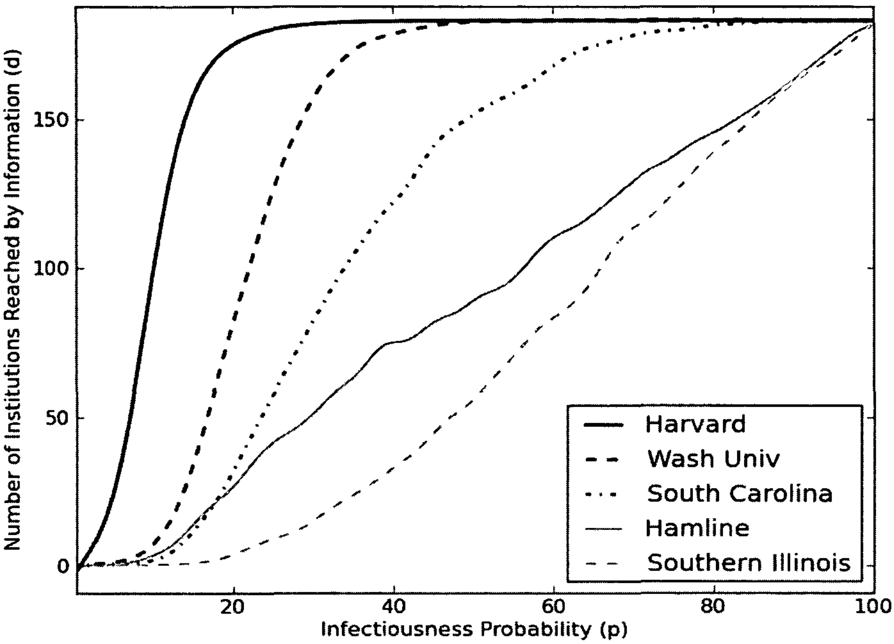
56. If anything, this decision should provide conservative estimates of historically elite schools, as these schools often place multiple faculty members at a given institution.

57. As noted earlier, differential host susceptibility, while often considered in the epidemiology literature, is not explicitly part of this model.

58. As we believe replication is a hallmark of the scientific enterprise, we will happily provide our Python code upon request. A Netlogo based implementation of the model is also available in the online supplement: http://computationallegalstudies.com/jle-law-prof-article/.

changes in the value of *p*. Yet, for many historically elite institutions diffusion is exponentially accelerated by their respective structural position within the broader network topology.[59]

Figure 6. Computational Simulation of Diffusion Based on the Structure of the American Legal Academy



VI. Conclusion

Extant scholarship has long considered topics such as the intersection of law and politics, including the appropriate role for the judiciary in a constitutional democracy.[60] Less often considered are the institutions collectively responsible for training and initially socializing nearly every lawyer and judge in the United States. While some argue that the modeling of large-scale social processes such as the rise of intellectual paradigms or the emergence of new

59. Appendix II offers an alternative presentation of the model. The x-axis displays the minimum transmission probability needed for each law school to infect s percent of all other schools, when that school is the only one infected and all others are susceptible at t = 0. The y-axis position of the school is its rank when s = 90 percent (denoted by a filled circle), where the school with the lowest minimum value of p is highest-ranked. The corresponding values of p for s = 50 percent and 25 percent are marked by "x" and "+", respectively.

60. *E.g.*, Robert Dahl, Decision-Making in a Democracy: The Supreme Court as a National Policy-Maker, 6 J. Pub. L. 279 (1958); Jeffrey A. Segal & Harold J. Spaeth, The Supreme Court and the Attitudinal Model (Cambridge 1993).

doctrinal approaches is analytically intractable, we believe it is possible to leverage developments in computational social science to better understand the mechanics of these phenomena.

There are undoubtedly a wide variety of actors and institutions whose complex interactions work to produce changes in the common law. We hope our analysis motivates additional theoretical and empirical analysis of legal socialization and its role in structuring the bounds of collective conception. In other words, despite the possibility that some subset of relevant social process might be difficult to define, we believe the inquiry into the machinery of cultural replication–mechanics classically described by scholars such as Duncan Kennedy–should continue.[61] The wider literature offers concrete descriptions of instances where the legal academy directly impacted the development of the American common law.[62] Building from this work, we believe studying the self-organization of such legal elites and their channels of diffusion is an important piece of a larger effort to move legal science toward a first law of jurisdynamics.

61. *See* Kennedy, *supra* note 54.

62. *E.g.*, Mark Graber, Transforming Free Speech: The Ambiguous Legacy of Civil Libertarianism (University of California 1991); and Brandwein, *supra* note 3 (2007).

Appendix 1. A Sample of the Data Set

School of Professorship	School ID	Professor Name	School of First American Law Degree	Law Degree| School ID
University of Michigan	9	Alicia_Davis_Evans	J.D. Yale	1
University of Louisville	99	Jim_Chen	J.D. Harvard	1
Florida State University	55	JB_Ruhl	J.D. Virginia	11
University of Virginia	11	G_Edward_White	J.D. Harvard	2
Cornell University	13	Michael_Heise	J.D. Chicago	6
University of Arizona	45	Ana_Maria_Merico	J.D. Michigan	9
Emory University	22	Frederick_Tung	J.D. Harvard	2
University of Texas-Austin	18	Sanford_Levinson	J.D. Stanford	3
Rutgers University-Camden	71	Robert_F_Williams	J.D. Florida	50
University of Wisconsin	33	Elizabeth_Mertz	J.D. Northwestern	12
University of Pennsylvania	7	Christopher_S_Yoo	J.D. Northwestern	12
Mercer University	100	Ted_Blumoff	J.D. Washington Univ.	19
Stanford University	3	Pamela_Karlan	J.D. Yale	1

Appendix II: Infectiousness Level P Necessary to Saturate the S percent Threshold of the Network