Hierarchical Sorting and Learning Costs:
Theory and Evidence from the Law

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Abstract

Garicano and Rossi-Hansberg (2003) show that knowledge-based hierarchies are characterized by positive sorting between workers and managers when knowledge acquisition takes place before production. We extend the analysis and find that complementarities between manager and worker skill are even stronger when knowledge is acquired on the job. We then examine empirically the existence of sorting in law firms along the dimensions of cognitive ability and experience. We find strong evidence of positive sorting by cognitive ability, as proxied by the quality of the law school attended, but little evidence of sorting by experience, suggesting little substitutability between cognitive ability and experience.

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1. Introduction

Production in human capital intensive industries consists, to a large extent, of problem solving. Efficient problem solving requires that agents acquire knowledge and be matched to problems they have a comparative advantage in solving. A central problem of organization in a human capital intensive context, therefore, is facilitating such matches, both because it exploits individuals' existing comparative advantages and because more efficient matching processes encourage further specialization.

In this paper, we first analyze theoretically how and why hierarchical organization in problem solving implies positive sorting with respect to human capital: managers with the lowest cost of acquiring knowledge or 'learning cost' work with workers with the lowest learning cost. We do this through a model of the optimal hierarchical structure of knowledge intensive production when knowledge must be acquired on the job. We then study empirically the dimensions upon which sorting takes place among lawyers. In so doing, we hope to illuminate both the role of hierarchies in matching individuals with each other and the properties that this matching must have, as well as more broadly some features of the optimal organization of specialized knowledge.

Garicano (2000) argued that hierarchical organization plays a key role in organizing the acquisition of knowledge when matching problems and solutions is costly. Hierarchies allow knowledgeable individuals to specialize in problems only they can solve while less knowledgeable individuals protect them from more routine problems. Garicano and Rossi-Hansberg (2003) show, in an equilibrium model of knowledge hierarchies with heterogeneous agents, that the use of such knowledge-based hierarchies results in the matching of workers with lower learning costs with managers with lower learning costs when knowledge acquisition takes place before production. We develop an extension of their model that allows us to apply it to the on the job training case relevant to law firms.[1]

We find that the existence of on-the-job training strengthens positive sorting between workers and managers. When managers are matched with workers, they

must incur two costs that depend on the characteristics of the workers: they must help workers whenever they cannot deal with the problems on their own, and they must allow workers time to train on the job. Lower learning cost workers are more valuable to more skilled managers for two reasons related to these two costs. First, as in the pre-market training set-up analyzed by Garicano and Rossi-Hansberg, more knowledgeable workers allow a more talented manager to leverage his knowledge adequately rather than distracting him with questions any other manager could have answered. Second, and this is the new effect we uncover, the opportunity cost of the time spent training increases the more knowledgeable the manager; thus a more knowledgeable manager benefits more from a worker with lower learning cost.

We then conduct an empirical analysis that investigates the existence and nature of positive sorting within law firms. Our data comes from the Martindale-Hubbell Law Directory (1993), which provides information on individual lawyers' human capital, their firms, and their position within their firm. This allows us to assess the degree to which sorting takes place along two dimensions: law school quality and experience. We find evidence of positive sorting between associates and partners associated with law school quality, but not experience. Associates disproportionately work at the same firm as partners who went to similarly-ranked schools, but there is little evidence that more experienced associates work at the same firm as more experienced partners. These empirical facts are consistent with the hypothesis that law firms are organized as knowledge-based hierarchies, and lawyers' learning costs are strongly correlated with their cognitive ability but not necessarily their experience. Further research is necessary to distinguish between this and other theories in which within firm sorting is associated with where individuals went to school. We also provide some results with respect to sorting among partners and among associates. As is the case when examining partner-associate matches, we find evidence that positive sorting among partners and among associates takes place along the lines of law school quality, but little evidence that it takes place along the lines of experience.

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[1] In Garicano and Rossi-Hansberg only pre-market investments are studied.

This study contributes to two theoretical literatures and two empirical literatures. A first theoretical literature studies sorting in both production and non-production contexts.[2] Theoretical work in this area includes Kremer (1993), who discusses the importance of sorting in situations where complementarities in production are strong, and Prat (2002), which extends these results to a more general framework. Methodologically, our paper is inscribed within the broad 'hedonics' tradition of Rosen (1974), Sattinger (1993) and Teulings (1995), which studies the assignment of individuals to objects (or places) and separates them according to their willingness to pay for marginal improvements in the allocation. Our paper is different in that, as in the recent paper by Garicano and Rossi-Hansberg (2003), individuals are matched to each other, rather than to any specific physical attribute.

Empirically, our paper contributes to the recent work on sorting and assignment. Again, this work is much richer in non-production contexts, notably marriage and racial segregation in neighborhood choice.[3] Empirical work studying sorting in production is scarce, probably due to the fact that heterogeneity of the positions that need to be filled and of the organizations that are the object of study make comparisons of the labor force hard to undertake. The recent development of matched employee-employer data sets has allowed for some empirical work on sorting in production (Haltwanger, at al. 1999) and will probably lead soon to more contributions on this area. Finally, our paper contributes to the literature on the organization of professional service firms, including Baumgardner's (1988) study of the division of labor among physicians, Galanter and Palay's (1991) study of incentives within legal hierarchies, Rosen's (1992) study of the labor market for lawyers, Heinz and Laumann's (1982) study of the social structure of the Chicago bar, and Garicano and Hubbard's (2003) study of law firms' field boundaries.

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[2] Less related to our work is the rich literature of sorting on non-production contexts; The seminal paper in this literature is Becker (1973). For a recent survey of this literature see Weiss (1997).
[3] On marriages, this literature in general finds positive sorting among spouses schooling and income in a multitude of countries, see for example Lam (1988) for a review. On sorting by race in residential choices see notably Cutler et al. (1999) for work documenting the extent and evolution of segregation in American cities.

The paper is structured as follows. Section 2 discusses the context of the legal industry. Section 3 develops the theory. Section 4 discusses the data. Section 5 presents the empirical analysis of the data. Section 6 concludes.

2. Human Capital and the Organization of Legal Services

Legal services are supplied by lawyers and their support staff. There is a sharp distinction between lawyers and support staff, in part because entry into the legal profession is highly regulated at the state level in the United States. All states require individuals to take and pass bar examinations in order to practice law, and most require individuals to have a degree from a law school accredited by the American Bar Association to take the exam. Some states allow lawyers who have passed another state's bar examination and practiced law in another state for some period of time to bypass the requirement that they pass their bar examination; for example, Texas allows lawyers who have practiced for at least five years in another state to apply for a waiver of the requirement that they take the Texas bar examination.

Lawyers accumulate human capital in two broad stages; first at law school, then on the job. There are roughly 180 accredited law schools in the United States ranging from highly prestigious institutions to non-selective schools that teach mainly part-time students. Admission to the most prestigious law schools is highly competitive. Admission committees evaluate prospective students on the basis of various factors, including especially their grades at their undergraduate institution and their score on a standardized test called the Law School Admission Test (LSAT). The latter, which assesses an individual's cognitive ability, is an extremely important factor in determining which schools accept a particular applicant. As a consequence, the law school an individual attends is correlated with their cognitive ability. We exploit this below when assessing the dimensions upon which lawyers sort within firms; we will use the ranking of the law schools that lawyers attend as a proxy for their cognitive ability.

Individuals obtain formal legal training at law school, usually from both general courses and courses in specific fields. This formal training is valuable

enough so that nearly all practicing lawyers have a law degree, even in states such as California where it is not a requirement. However, lawyers obtain a large share of their human capital on the job. Production of legal services in large part involves problem-solving. While problems have idiosyncratic elements, learning the solution to a problem can help a lawyer solve other, related problems as well. Experience thus can enhance lawyers' human capital.

As we discuss in detail in Garicano and Hubbard (2003), many lawyers specialize *horizontally* in a particular area of the law, such as corporate law, criminal law, environmental law, family law, patent law, real estate law, and many others. Concentrating on a particular field allows them to become "narrower, but deeper;" they learn how to solve more complicated problems within their specific field. When this happens, it is valuable for such lawyers to specialize in only difficult problems within their field. Lawyers' ability to do so depends, in part, on the efficiency of the process through which lawyers are matched to problems.

Most lawyers in the United States work in law firms that supply legal services to outside businesses and individuals.[4] These range from single-lawyer firms to firms with hundreds of lawyers. Law firms differ in their hierarchical organization. In some, all lawyers are at the same level; all are *partners*. In others, lawyers are distinguished by whether they are *partners* or *associates*.[5] *Partners* are generally the most knowledgeable and highest-skilled of the lawyers working within a particular firm and engage directly with clients. *Associates* are generally less experienced than partners, with less direct interaction with clients than partners, and they tend to be assigned tasks that do not require as highly-specialized knowledge as partners. Associates usually are individuals who are starting their careers as lawyers and generally face an up-or-out promotion decision at the end of 5-10 years,

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[4] In 2000, the Bureau of Labor Statistics' Industry-Occupation Employment Matrix reports that about 80% of lawyers worked out of law offices, 13% worked for a Federal, state, or local government, and 7% worked as "in-house counsel" for firms not specializing in legal services.
[5] There are also finer distinctions within these classes, for example, equity and non-equity partners. We do not elaborate on this because our data only distinguish between partners and associates.

depending on the firm. There are some exceptions to this, as some firms employ associates with more than ten years' experience.[6]

As human-capital intensive enterprises, a central problem law firms face is acquiring and organizing the human capital necessary to address clients' problems. We study this problem, and its implications, next.

3. Sorting in Knowledge Hierarchies

Our starting point in studying hierarchies in law firms is Garicano (2000) and Garicano and Rossi-Hansberg (2003), who develop a theory of how such an organization, interacting with the labor market supply of skill, jointly determines the assignment of tasks, the wage structure, and hierarchical structure within a particular area of expertise. Garicano's analysis builds from the observation that, within each particular area of expertise, what constrains the amount of specialization is the cost of discovering who knows what and of matching problems with individuals who know their solutions. Garicano shows that under these circumstances a "knowledge-based hierarchy" is the efficient way to organize the acquisition of knowledge. The role of the hierarchy is to increase the utilization rate of the knowledge of the most knowledgeable workers: hierarchies spread this knowledge over a wide range of less knowledgeable workers and shield knowledgeable workers from problems that less knowledgeable workers can solve equally well.

In what follows, we develop a model that, like Garicano and Rossi-Hansberg (2003), extends Garicano (2000) to a situation where agents have heterogeneous learning costs. However, in accordance with our empirical context, we extend the model to a situation in which the knowledge required for production to take place is acquired through on the job training rather than pre-market investments. The model below is simpler than Garicano and Rossi-Hansberg (2003); we restrict the analysis to organizations with at most two layers because our data only distinguish between partners and associates. We also simplify the characterization of the model in that

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[6] At large firms, these individuals are usually "off the partner track" lawyers.

instead of fully characterizing the equilibrium, we only investigate the property that we examine empirically: equilibrium sorting between partners and associates.

As in Garicano and Rossi-Hansberg (2003), we proceed by first analyzing the optimal configuration of workers and managers for a given wage structure, then characterizing the equilibrium configuration of teams, including the "assignment" of workers to managers. After setting up the model and characterizing the hierarchies that are formed, we analyze an important characteristic of the equilibrium configuration, the existence of positive sorting between workers and managers.

3.1 Problem Solving and Hierarchy When Knowledge Is Acquired On the Job

Consider a situation where production involves problem solving. Suppose all problems are equally valuable to solve, but that some problems arise more frequently than others. Let $F(z)$ equal the cumulative distribution of problems. Let higher z's be associated with rarer problems; thus, $f'(z)<0$, where $f(z)$ is the density function associated with the distribution.

Suppose that individuals can be assigned to two positions: they can be workers or managers. As we discuss later, such an assignment is an equilibrium when each individual prefers the position he or she is in to the alternative. Each individual is endowed with one unit of time. The supply of these individuals is limited and given by an exogenously-determined distribution of learning costs.

a. Workers' Time: Production and Training

Workers encounter and solve problems. They can learn the solution to problems in two ways: learning it themselves (i.e., training) or asking a manager once the problem arises.

Workers' time is allocated between production and training. Let t equal the time a worker spends in production, and assume that a worker spending t time in production encounters t problems. Assume that the time cost of learning problems in the interval $[0, z_p]$ is equal to $c_p z_p$. Workers' time constraint implies that workers who learn to solve problems up to z_p spend $(1 - c_p z_p)$ of their time in production.

These workers solve $F(z_p)$ of the problems they encounter themselves and ask for help on $1-F(z_p)$.

b. The Manager's Time: Helping Workers with Exceptions

The manager's time is spent acquiring knowledge and dealing with the exceptions resulting from the problems workers confront. For now, assume that it takes $h < 1$ of his or her time to answer a question, regardless of whether he knows the answer or not. Thus, the manager spends $h(1-F(z_p))$ in time answering each worker's questions; thus, the time cost of supervising *n* equally-trained workers is $nh(1 - F(z_p))$.

Intuitively, the number of workers a manager can supervise is limited by two things: the knowledge of the workers and how many questions the manager can answer per period. This time constraint contains a straightforward, but important implication: *managers can supervise more workers when workers are more knowledgeable.* The reason for this is simple: when a worker is more knowledgeable, he or she needs less help, so the manager has time to help more workers and to help solve more problems.

It also follows that holding managers' helping costs *h* constant, choosing workers' knowledge level determines how many workers the manager will supervise, and vice-versa. This implication simplifies the analysis because it means that if one knows how knowledge levels should change, one also knows how managers' "span of control" should change, and vice-versa. One can therefore pick whichever is easier to analyze.

Let the manager's cost of learning problems up to and including z_m be $c_m z_m$. The fraction of problems that the manager can solve is $F(z_m)$. It must be the case that, since $z_m > z_p$, $c_m < c_p$; managers have lower learning costs per-problem than workers.[7] This difference might reflect differences in either cognitive ability or

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[7] If this were not the case, it would be Pareto improving to switch managers and workers.

experience.[8] Then the time cost of learning z_m problems for the manager is $(1 - c_m z_m)$.

The time constraint of the manager is then

$$nh(1 - F(z_p)) + c_m z_m = 1.$$

Solving for n, the time constraint can be written as

$$n = \frac{(1 - c_m z_m)}{h(1 - F(z_p))}. \tag{1}$$

c. The Objective Function

The organizational problem is to choose workers' knowledge levels (or equivalently, the number of workers per manager) and the manager's knowledge level in order to maximize profits after wages, subject to workers' and the manager's time constraints. The teams produce whenever either workers or the manager knows the solution to the problem; since worker knowledge is a subset of manager knowledge, the total value of production is $F(z_m)nt$. The objective function of a manager who must pay a wage w=w(c_p) per worker of learning cost c_p and can choose his own and workers' training is

$$\max_z R = F(z_m)nt - wn = F(z_m)(1 - c_p z_p)n - wn$$

where *n* is subject to the time constraint (1) above and *z=(z_p,z_m)*. That is, the managers' objective can be written

$$\max_z R = \left(F(z_m)(1 - c_p z_p) - w\right)\frac{(1 - c_m z_m)}{h(1 - F(z_p))}. \tag{2}$$

Maximizing this objective function with respect to z_p and in z_m yields a pair of solutions z_i *(w, h, c_p, c_m)* for *i=p, m*.[9] Since this paper is only concerned with the

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[8] In other words, and consistently with what happens in professional services, a reason why the managers have lower cost of learning may be that they have already been workers and know some of the problems by the time they are managers.
[9] The problem is well behaved, and the solution is an optimum, as can be found by checking signs of the Hessian of this problem.

existence of sorting in equilibrium, we only derive comparative statics that are relevant to sorting.

The first order condition for workers' knowledge is given by

$$\frac{f(z_p)}{1-F(z_p)}\left(F(z_m)(1-c_p z_p)-w\right) = c_p F(z_m).$$ (3)

Intuitively, the marginal benefit of increasing workers' knowledge is that they need the manager less often, relaxing the time constraint of the manager and allowing him to increase his span of control. The left hand side of this equation depicts the marginal benefit of training a worker. Training this worker more means that he or she will ask slightly fewer questions, and will therefore enable the manager to supervise more workers. This value is composed of two terms. The first term depicts how many new workers are hired when one worker is trained more. This is given by the drop in the time cost of the worker: the decrease in the time the manager spends answering the worker's questions. This decrease is given by the hazard rate $f(z_p)/(1-F(z_p))$. The second term is benefit of an additional worker, which is given by the net output from the extra worker less the wage cost.

The marginal cost of training an individual worker is that he or she spends less time in production. This cost is given by the loss in production time c_p times the output a worker could have obtained in this time, which is given by the manager's knowledge.

Similarly, the first order condition for manager knowledge is given by:

$$f(z_m)(1-c_p z_p)(1-c_m z_m) = \left(F(z_m)(1-c_p z_p)-w\right)c_m$$ (4)

The left hand side is the marginal benefit of increasing the manager's knowledge, given by the extra questions he is able to answer. The cost is the drop in production that results from a decrease in his available time, which is given by the time cost c_m times the net output per unit of time $\left(F(z_m)(1-c_p z_p)-w\right)$.

To derive the positive sorting result, we obtain the comparative statics with respect to the optimal knowledge levels for workers and the manager when the cost of managerial learning decreases. The next proposition shows that as the manager's learning costs decrease, optimal knowledge levels for both workers and managers increase. Intuitively, a manager with lower learning cost will acquire more knowledge himself and will want his workers to acquire more knowledge so that he can better leverage his talent.

Proposition 1. *A decrease in learning costs for managers leads optimal knowledge levels for both managers and workers to increase.*

Proof: See Appendix

3.2 Equilibrium Sorting Between Workers and Managers

Substituting in the expression for managerial rents (2) the optimized values of $z_p(c_p,c_m,w)$ and $z_m(c_p,c_m,w)$ obtained by solving the first order conditions (3) and (4), we obtain the rents that a manager obtains as a function of the workers he is sorted with and of his own learning cost, $R(c_p,c_m,w)$. Given this function, we can characterize the market equilibrium. Here we will discuss only briefly the most important aspects of the equilibrium,[10] and focus on the existence of sorting between workers and managers. Sorting relies on the existence of complementarities in production between managers' and workers' knowledge. We proceed by briefly describing an assignment of workers to managers involving positive sorting in this context. We then show that positive sorting is indeed a necessary condition for the market equilibrium to exist.

Assume that the density function for the learning cost of individuals, c, is $\varphi(c)$, with support $[\underline{c}, \overline{c}]$. Positive sorting means that more skilled workers are matched with more skilled managers. If such an assignment exists, then there must exist a function C such that $c_m = C(c_p)$, i.e. that matches the learning costs of

managers and workers. This function can be defined by the equilibrium condition that at every point $c*$ in the distribution of learning costs, the proportion of workers that are supplied be equal to the proportion of workers that the managers demand.

$$\int_{\underline{c}}^{C(c*)} \varphi(c)dc = \int_{\underline{c}}^{c*} n(c)\varphi(c)dc \qquad (5)$$

where n(c) is the span of managers as given by substituting the optimal $z_p(c,C(c),w)$ and $z_m(c,C(c),w)$ in equation (1), and ĉ is the cutoff between managers and workers such that all workers with learning cost higher than ĉ are workers and all those with costs lower than ĉ managers. Intuitively, the right hand side of (5) is the demand by managers between the best manager and a given manager at $c*$; the left hand side is the supply of workers between the best worker (who has skill ĉ) and the worker that corresponds to manager $c*$, that is the worker with learning cost $C(c*)$. Equilibrium requires that this supply and demand be equal.

Moreover, for this assignment to be an equilibrium it is necessary that the wage function that supports it be such that the assignment is optimal for each manager: i.e., it must be the case that the manager has no incentive to hire a worker with a higher or a lower skill level than the one we have tentatively assigned. This requires that the wage differential among workers must be such that each manager's rents are maximized precisely at the point predicted by the tentative assignment. Taking the optimized managerial rents from equation (2) and applying the envelope theorem:

$$\frac{\partial R}{\partial c_p} = 0 \iff -z_p F(z_m) - w'(c_p) = 0 \qquad (6)$$

This equation means that, for the wage function $w(c_p)$, the marginal cost of an increase in skill, given by the change in wage, must be equal to the marginal benefit of an increase in skill, given by the reduction in costs that hiring this worker produces for the team. The reduction in costs due to the lower learning costs is given

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[10] The reader interested in a more complete discussion is referred to Garicano and Rossi-Hansberg (2003) where the equilibrium is fully characterized, albeit in a model with pre-market (as opposed to

by what the worker learns times the money cost per unit of time lost. We can then obtain from differential equation (6) the wage-learning cost relationship $w(c_p)$ for workers that must hold in equilibrium, together with a terminal condition that equalizes the wage of the marginal worker with the rents earned by the marginal manager:

$$w'(c_p) = -z_p F(z_m)$$
$$w(\hat{c}) = R(\hat{c}, \bar{c}, w(\bar{c})) \tag{7}$$

Intuitively, the second condition of (7) equalizes the wage of the marginal worker (the best worker, who has learning costs $\hat{c}$) and the earnings of the 'worst manager' who is a manager with learning cost $\hat{c}$, who is matched with the worst possible worker with skill $\bar{c}$ and pays him a salary $w(\bar{c})$.

Finally, agents choose occupations to maximize their utility given their learning costs:

$$U(c) = max\{w(c), R(C^{-1}(c), c, w(C^{-1}(c))\}$$

After sketching the equilibrium in this economy, we can now show that positive sorting is indeed a characteristic of the equilibrium.

Proposition 2. *In a problem solving economy with on the job training, the equilibrium is characterized by positive sorting between managers and workers along the dimension of learning costs.*

Proof.

The first order condition for optimality requires that $dR/c_p = 0$. Taking the full derivative of this condition we have that:

$$\frac{\partial^2 R}{\partial c_p^{\,2}} + \frac{\partial^2 R}{\partial c_p \partial c_m} \frac{dc_m}{dc_p} = 0 \tag{8}$$

on the job) training.

Since the second derivative is negative by optimality of the assignment, we have positive sorting ($dc_m / dc_p > 0$) if and only if the cross derivative is positive. Taking derivatives in (6) and using the optimality of the wage function in (6), the cross derivative is given by:

$$\frac{\partial^2 R}{\partial c_p \partial c_m} = -\left[F(z_m)\frac{dz_p}{dc_m} + z_p f(z_m)\frac{dz_m}{dc_m} \right] n \qquad (9)$$

Since, by Proposition 1, both of the derivatives inside the expression are negative, we have that the cross derivative is positive and only an assignment with positive sorting can be sustained in equilibrium.

$$\frac{dc_m}{dc_p} = -\frac{\dfrac{\partial^2 R}{\partial c_p^{\,2}}}{\dfrac{\partial^2 R}{\partial c_p \partial c_m}} > 0 \qquad (10)$$

□

Thus the result in Garicano and Rossi-Hansberg (2003) that positive sorting takes place in equilibrium is robust to the introduction of on the job training. In fact, the complementarity leading to sorting is stronger in this case than it is when only pre-market investments are considered. When knowledge is acquired pre-market, the only term in the cross-derivative is dz_p/dc_m. Here however, there is an additional reason for positive sorting, captured by the additional term in the cross derivative (9): $z_p f(z_m)\, dz_m/dc_m$.

To understand this term, it helps to look at expression (6) to see its origin. That expression equalizes the marginal value of a worker with a lower learning cost worker to its marginal (wage) cost. Better workers are valuable because they can acquire knowledge at a lower cost as measured by the production time lost. This marginal value is higher when the manager's learning cost is lower for two reasons. The first one exists whether training is on the job or pre-market (see Garicano and Rossi-Hansberg (2003)); workers assigned to a knowledgeable manager acquire more knowledge since this allows the manager to leverage his knowledge better by specializing in solving problems he has a comparative advantage in addressing.

Intuitively, knowledgeable managers demand that their workers acquire more knowledge as their time is more valuable. The second has to do with the opportunity cost of workers' learning: they spend less time in production. This opportunity cost is highe when the manager is more knowledgeable since time lost in production would have yielded more output with a more knowledgeable manager. Since managers with lower learning costs acquire more knowledge ($dz_m/dc_m < 0$), such managers benefit more from lower-learning-cost workers who sacrifice less production time in acquiring a given level of knowledge. Both of these effects make workers with low learning costs particularly valuable to managers with low learning costs

We will examine Proposition 2 empirically by examining whether there is evidence of positive sorting between partners and associates in law firms. If learning costs are highly correlated with cognitive ability, one would expect that sorting would take place along the lines of law school attended: partners who attended highly ranked schools should work at the same firm as associates in highly ranked schools, and partners who attended lower-ranked schools should work at the same firm as associates in lower-ranked schools. If learning costs are highly correlated with experience, one would expect that sorting between partners and associates would take place along the lines of experience: partners with more experience should work at the same firm with more-experienced associates.

We will also examine whether there is evidence of positive sorting among partners and among associates within the same firm. We do this in large part to generate additional facts about how human capital is organized within firms. Although the theory presented here does not directly address the issue of which partners work with one another in the same firm, under some conditions positive sorting in our model exists among partners as well as between partners and associates. For example, if partners are recruited through internal promotion, partner-partner sorting will be along the same dimensions as partner-associate sorting. Positive sorting between partners may also be an implication of other theories, such as Kremer (1993) and Levin and Tadelis (2002). Our empirical results

document patterns in sorting; more research is needed to distinguish among these theories.

4. Data

The data are from the 1993 Martindale-Hubbell Directory of Lawyers for the state of Texas. The data are taken from the directory's "blue pages;" these "blue page" listings, like those in the "white pages" in phone directories, are unpaid and provide a close-to-comprehensive list of lawyers.[11] Martindale-Hubbell obtains lists of lawyers from a variety of sources, including state and local bar associations, and collects information from individual lawyers and law firms. The blue page listings contain basic data about individual lawyers, including their name, their undergraduate institution and graduation year, the school where they obtained their law degree, the year they first passed a state bar examination, and the name and address of the firm at which they work. Our analysis below includes only lawyers in private practice; we exclude all lawyers working as in-house counsel, judges, law professors, and other positions outside of law firms.

We then created a firm-level dataset, grouping lawyers by the firms in which they work. Since our analysis is concerned only with the matching of lawyers within firms, we work with subsamples of the data where matching is relevant. When investigating matching between partners and associates, our subsample includes the 990 firms in our data with at least one partner and at least one associate. This data set includes 6132 partners and 4409 associates. Similarly, when exploring matching among partners (associates), we use a subsample that includes the 1523 (660) firms in our data with at least two partners (associates), with 8372 (4205) lawyers.

Our analysis focuses on the sorting of lawyers according to the quality of the law school they attended, and according to their experience. Using the 2001 US News and World Report rankings as a guide, we divide U.S. law schools into four tiers. Examples of law schools in these four tiers are the University of Chicago,

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[11] Like telephone books, the Martindale-Hubbell directory contains a section of unpaid listings designed to provide a comprehensive list of lawyers and a section of paid listings (Martindale-Hubbell's "white pages") that provide more detail of individual law firms' practices.

University of Texas-Austin, Louisiana State University, and Texas Southern University, respectively. Analogously, we divide lawyers into four experience categories, according to whether they have five or fewer, six to ten, eleven to fifteen, or more than fifteen years of experience, as measured by the number of years since they first passed a state bar examination. Table 1 contains counts of the number of partners and associates, by law school tier and experience category, for each of our subsamples.

5. Empirical Analysis

5.1. Measuring Human Capital Sorting in Law Firms

a. Sorting between partners and associates

Our first empirical task will be to measure the extent to which associates work at the same firm with partners who attended the same and different tier law schools. Constructing such a measure requires determining a baseline of comparison: when do we find unusually high sorting? We develop a statistic that measures the extent to which associates who attended Tier j law schools work at the same firm as partners who went to Tier j' law schools, above and beyond the extent they would if the educational composition of associates at each firm were the same as that across the entire state of Texas.

Our measure for how associates are matched to partners is constructed as follows.[12] Let N_i^a be the number of associates in law firm i and n_i^{ja} be the number of those associates who attended a Tier j law school. The share of associates in the entire state of Texas who went to a Tier j law school, s^{ja}, is thus

$$s^{ja} = \frac{\sum n_i^{ja}}{\sum N_i^a}$$

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[12] One can construct analogous statistics for how partners are matched to associates: to what extent do partners who went to Tier j law schools work with associates who went to Tier j' law schools?

where here and throughout, the sums are taken over i (firms in Texas). For any given pair of Tiers j and j', we aim to measure share of the Tier j associates who work with the average Tier j' partner, above and beyond what this share would be if this share was s^{ja} at all firms. Thus, for any given pair of Tiers j and j', this statistic is

$$S_{pa}{}^{jj'} = \frac{1}{s^{ja}} \sum \frac{n_i^{j'p}}{\sum n_i^{j'p}} \frac{n_i^{ja}}{N_i^a} .$$

The term in the outer sum is a weighted average of share of the associates in firm i that went to a Tier j law school, where the weights are the share of Tier j' partners in the state of Texas that work at firm i. Therefore, the sum yields the share of Tier j associates that work in the firm of the average Tier j' partner. Normalizing by s^{ja} normalizes this weighted average by the share of associates in the state of Texas who attended a Tier j law school.

The scale of the statistic is such that $S^{jj'} = 1$ if the average Tier j' partner works with exactly the same share of Tier j associates as Tier j associates' population share. If $S^{jj'} = 1.30$, this means that the average Tier j' partner is 30% more likely to work at the same firm as a Tier j associate than what would be implied by the population shares.

We use analogous statistics to analyze matching between partners and associates according to experience categories.

b. *Sorting among partners and among associates: who are your peers?*

We measure the extent of sorting within hierarchical levels in a way analogous to above, except that we subtract the contribution of the lawyer himself to preserve the interpretation that we are assessing the composition of a lawyer's colleagues. This produces statistics that measure sorting among peers: for example, what share of the average Tier i partner's peers within his firm also attended Tier i law schools?

When Tiers j and j' are different tiers, the statistic is

$$S_{pp}{}^{jj'} = \frac{1}{s^{jp}} \sum \frac{n_i^{j'p}}{\sum n_i^{j'p}} \frac{n_i^{jp}}{(N_i^p - 1)} \ .$$

When Tiers j and j' are the same tier, we have

$$S_{pp}{}^{jj'} = \frac{1}{s^{jp}} \sum \frac{n_i^{j'p}}{\sum n_i^{j'p}} \frac{n_i^{jp} - 1}{(N_i^p - 1)} \ .$$

These statistics measure the composition of a Tier j partner's peers relative to what it would be if composition of his peers were the same as that when considering all partners in the state of Texas. As before, if the statistic equals $1 + X/100$, this means that a Tier j partner's peers are X% more likely to be have attended a Tier j' school than if all law firms had the same educational composition as the population shares. We construct analogous measures for associates and, as above, for both school tiers and experience categories.

5.2. Empirical Results

a. Sorting between Partners and Associates

<u>Sorting by school quality</u>

Table 2 examines the school tier sorting of partners with associates. It has two panels. Panel A investigates the composition of associates in the average partner's firm. Panel B investigates the converse, the composition of partners in the average associate's firm.

Each panel has two parts, leading to the construction of the normalized share $S^{jj'}$ described above. The first part computes the average educational composition of associates for different educational classes of partners. For example, the first column reports the composition of associates in the average Tier 1 partner's firm. Averaged across Tier 1 partners, 16% of associates are from Tier 1 law schools, and 49%, 16%, and 19% are from Tier 2, 3, and 4 schools, respectively. Reading across the table, partners who attended higher-ranked law schools are more likely to work with Tier 1 associates, and less likely to work with Tier 4 associates, than partners who attended lower-ranked law schools.

The second part of the table reports the normalized shares, $S^{jj'}$, which are computed by dividing the numbers in the first four columns by the corresponding number in the fifth. The normalized share of 1.70 (0.16/0.09) reported for S^{11} indicates that Tier 1 partners are 70% more likely to work with Tier 1 associates than what would be predicted by the population shares.

What does Table 2 tells us? The results are striking in their consistency. First, with the exception of S^{22}, the diagonal terms are larger than their associated off-diagonals: firms where Tier j partners work are disproportionately comprised of Tier j associates. Partners and associates match according to the quality of their law school. Second, the off-diagonals decline as one moves away from the diagonal. Partners and associates attending different-tier law schools are less likely to work at the same firm with each other as the difference in their law schools' ranking increases. These results suggest that partner-associate sorting is along the lines of cognitive ability.

Panel B provides similar results. Firms where Tier 1 associates work are disproportionately composed of Tier 1 partners: the normalized share of partners is 2.51 (0.23/0.09), indicating that a Tier 1 associate is 150% more likely to work with a Tier 1 partner than if the educational shares of partners were uniform across Texas law firms. In contrast, Tier 4 associates' firms tend to be disproportionately composed of Tier 4 partners. As in Panel A, the diagonal terms tend to be larger than the associated off-diagonals, and the off-diagonals tend to decrease as one moves away from the diagonal.

Taking Panels A and B together, the results of this table provide evidence of positive sorting between partners and associates by school tier. While there are other possible interpretations of this general result,[13] it is consistent with the view that hierarchies within law firms address the problem of organizing knowledge and that learning costs are correlated with cognitive ability.

<u>Sorting by experience</u>

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[13] For example, a sociological interpretation might focus on social networks that form around law school ties.

The interpretation and structure of Table 3 is identical to Table 2, except that now the question concerns the matching of lawyers in different experience categories. Panel A is striking in its contrast to the panels in Table 2. Moving across the table, the columns are quite similar. The experience profile of associates varies little with the experience profile of partners. In each column, 65-70% of associates have less than five years experience, and 20-23% have between six and ten years experience. These two rows are the most economically meaningful since the vast majority of associates have ten or less years of experience. The figures in the bottom two rows are all low, indicating the small fraction of associates who have more than of ten years experience. The highest of these figures is in the lower left: firms with very inexperienced partners have a disproportionately high number of associates.[14]

We thus find little evidence of partner-associate sorting along the experience dimension. This result is of interest in light of the theory described above. If partners and associates match with each other on the basis of learning costs, heterogeneity in learning costs among lawyers appears to be much more strongly related to lawyers' cognitive ability than their experience.

b. Sorting within partners and within associates

Sorting by School Quality

Table 4 presents our findings of sorting among partners and among associates. The findings are again striking. In both cases, we observe positive sorting along the dimension of law school quality. In the case of partners of tier 1, $S^{11}=2.49$: a Tier 1 partner's peers are 150% more likely to be Tier 1 lawyers than if the educational composition of partners within each firm was the same as that in the economy. Similarly, Tier 2, 3, and 4 lawyers are all more likely to work with peers

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[14] This result is likely driven by a very small number of matches between partners and associates: only 5 percent of partners in this sample have five or fewer years of experience, and only 3 percent of associates have more than fifteen years of experience. The robustness of this result is thus questionable, which is why we do not emphasize it.

who went to the same tier law schools. The bottom panel shows that similar patterns hold when considering matching among associates.

 Sorting by experience.

Table 5 presents measures of experience sorting. As in Table 3 for the case of between category sorting, we find the sorting patterns are weaker for experience than school tier. One exception exists, however. The 2.40 figure reported in the upper left corner indicates that inexperienced partners' peers tend to be inexperienced as well.

Panel B repeats the exercise for associates. As before, experience sorting is generally weaker than educational sorting. As in Panel A, there is an exception. The 5.40 figure in the lower left indicates that associates with more than 15 years experience tend to work at the same firms as other associates with more than 15 years experiences. Very experienced associates tend to work at the same firms with one another.

6. Conclusions

This paper makes two contributions toward understanding the organization of human capital. First, we show theoretically that hierarchical organization generates positive sorting in a context where individuals acquire knowledge on the job. To do this we extend the model of knowledge hierarchies with pre-market training in Garicano and Rossi-Hansberg (2003). The logic for our finding is as follows. A manager incurs two types of costs when he works in a knowledge-based hierarchy: first, he must help workers whenever they do not know problems' solutions; second, he must allow the workers to spend time learning at the cost of production time. This second cost appears only in a model with on-the-job training. Workers with low learning costs are particularly valuable for managers with low learning costs as a consequence because they allow such managers to exploit increasing returns from knowledge at a lower cost than workers with higher learning costs. Other models and theories, including some in sociology, suggest reasons for positive sorting. We view the strength of the model in illuminating why this link would be particularly strong in knowledge-intensive production. We show how and why the problem of

efficiently acquiring and utilizing knowledge leads to the matching of more able workers with more able managers.

Second, we document the extent and nature of sorting in one particular human capital intensive industry, the legal services industry. We uncover three notable patterns in the data. First, partners tend to be matched with associates who attended the same quality law school and vice versa. This sorting is a strong and robust feature of our data. Second, there is little evidence of sorting by experience: there is no evidence that more experienced partners work with more experienced associates. Partner-associate matches take place along the lines of law school quality, not experience. Third, the within lawyer category results (within partners and within associates) for both school tier and experience reflect broadly these same patterns.

In our view, these sorting patterns, viewed through the lens of the model in section 3, suggest some possible features of the process by which knowledge is acquired and utilized in law firms. In particular, if we take seriously the idea that sorting takes place along the "cost of learning to solve problems" dimension emphasized by the model, the patterns in the data show very little substitution between cognitive ability and experience. Associates who attended a top law school are disproportionately likely to work with partners who attended a top law school, and associates who attended less-selective schools are disproportionately likely to work with partners who attended less-selective schools. On the other hand, a more experienced associate is not significantly more likely to be matched with a more experienced partner.

This type of pattern would be consistent with a world in which teams of lawyers with different cognitive abilities are matched with problems of different difficulty and where experience affects lawyers' position within these teams but not which problems they are involved in solving. While a hypothesis along these lines would be consistent with the patterns observed, research that investigates relationships between lawyers' human capital, wages, productivity, and organizational form is necessary to provide more definitive evidence on this hypothesis.

The patterns we uncover open up several other questions that we will address in future work. First, what are the implications of these sorting patterns for the earnings structure of lawyers? How does sorting affect the level of wage inequality observed in the market? Second, is it the case, as the model presented above would imply, that more skilled partners have a larger span and that this span is larger when they are matched with more highly skilled associates? Finally, how do changes in the returns to specialization affect these patterns? In particular, does market size affect the extent to which we observe sorting?

References

Baumgardner, J. R., 1988. Physicians' Services and the Division of Labor Across Local Markets. Journal of Political Economy 96, 948-982.

Becker, G. S.,1973 A Theory of Marriage: Part I. Journal of Political Economy 81, 813-846.

Cutler, D. M., Glaeser, E. L., Vigdor, J.L., 1999. The Rise and Decline of the American Ghetto. Journal of Political Economy 107, 455-506.

Galanter, M., Palay, T., 1991. Tournament of Lawyers: The Transformation of the Big Law Firm. Chicago: University of Chicago Press.

Garicano, L., 2000. Hierarchies and the Organization of Knowledge in Production, Journal of Political Economy 108, 874-904.

Garicano, L., Hubbard, T.N., 2003. Specialization, Firms and Markets: The Division of Labor within and between Law Firms. NBER Working Paper 9719.

Garicano, L., Rossi-Hansberg, E., 2003. Organization and Inequality in a Knowledge Economy. Working Paper. University of Chicago.

Haltiwanger; J. C., Lane, J.I., Spletzer, J. R., 1999. Productivity Differences across Employers: The Roles of Employer Size, Age, and Human Capital. The American Economic Review 89, 94-98.

Heinz, J. P., Laumann, E.O., 1982. Chicago Lawyers: The Social Structure of the Bar. Evanston: Northwestern University Press.

Kremer, M., 1993. The O-Ring Theory of Economic Development. Quarterly Journal of Economics 108, 551-75.

Lam, D.,1988. Marriage Markets and Assortative Mating with Household Public Goods: Theoretical Results and Empirical Implications, Journal of Human Resources, 23, 462-487.

Levin J. Tadelis S., 2005. Profit Sharing and the Role of Professional Partnerships. Quarterly Journal of Economics 120 131-171.

Martindale-Hubbell Law Directory, 1993. Summit, N. J.: Martindale-Hubbell, inc.

Prat, A., 2002. Should a Team Be Homogeneous? European Economic Review 46, 1187-1207.

Rosen, S., 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. Journal of Political Economy 82, 34-55.

Rosen, S., 1992. The Market for Lawyers. Journal of Law and Economics 35, 215-46.

Sattinger, M, 1993. Assignment Models of the Distribution of Earnings. Journal of Economic Literature 31 831-880.

Teulings, C. N., 1995. The Wage Distribution in a Model of the Assignment of Skills to Jobs. Journal of Political Economy 103, 280-315

Weiss, Yoram. Weiss, Y., 1997. The Formation and Dissolution of Families. Why Marry, Who Marries Whom, and What Happens Upon Marriage and Divorce? In: Rosenzweig, M.R., Stark, O. (Eds.) Handbook of Population and Family Economics. Amsterdam: Elsevier Science

Appendix

Proof of Proposition 1 (Comparative Statics)

Start by substituting the time constraint (1) in the objective function (2) to have

$$\max_{z} R = \left(F(z_m)(1-c_p z_p) - w \right) \frac{(1-c_m z_m)}{h(1-F(z_p))}.$$

The two first order conditions dR/d$\mathbf{Z}$ =0 are

$$\frac{1}{h(1-F(z_p))}\left(f(z_m)(1-c_p z_p)(1-c_m z_m) - y c_m \right) = 0 \text{ and}$$

$$n\left(\frac{f(z_p)}{1-F(z_p)} y - c_p F(z_m) \right) = 0,$$

where, to simplify, we call y=$\left(F(z_m)(1-c_p z_p) - w \right)$. Call the first order conditions f_1 and f_2. Their derivative with respect to c_m parameters is, after some small manipulation,

$$\begin{pmatrix} df_1 / dc_m \\ df_2 / dc_m \end{pmatrix} = \frac{1}{h(1-F(z_p))} \begin{pmatrix} -\dfrac{1}{c_m} f(z_m)(1-c_p z_p) \\ 0 \end{pmatrix},$$

and the Hessian is (substituting in the first order conditions where possible).:

$$H = \frac{1}{h(1-F(z_p))} \begin{pmatrix} \left((1-c_p z_p)(-2c_m f(z_m)+(1-c_m z_m)f'(z_m))\right) & c_p\left(-f(z_m)(1-c_m z_m)+F(z_m)c_m\right) \\ c_p(F(z_m)c_m - (1-c_m z_m)f(z_m)) & nyf'(z_p) \end{pmatrix}$$

.

The comparative statics are given by

$$\begin{pmatrix} dz_m / dc_m \\ dz_p / dc_m \end{pmatrix} = 1/|H| \begin{pmatrix} \dfrac{ny}{c_m} f'(z_p)f(z_m)(1-c_p z_p) \\ -c_p f(z_m)w \end{pmatrix}.$$

Since f'<0 and 1/|H|>0 by the SOC, we have that dz_m/dc_m<0 and dz_p/dc_m<0.

Table 1
Number of Partners and Associates by Law School Tier and Experience

	Sample 1	Sample 2	Sample 3
Partners	6132	8372	
Law School Tier 1	557	639	
Law School Tier 2	3382	4443	
Law School Tier 3	939	1375	
Law School Tier 4	1254	1915	
Experience: 0-5 Years	336	589	
Experience: 6-10 Years	1270	1700	
Experience: 11-15 Years	1527	2056	
Experience: 16+ Years	2999	4027	
Associates	4409		4205
Law School Tier 1	409		408
Law School Tier 2	2142		2058
Law School Tier 3	751		722
Law School Tier 4	1107		1017
Experience: 0-5 Years	3100		2980
Experience: 6-10 Years	988		932
Experience: 11-15 Years	190		176
Experience: 16+ Years	131		117

Sample 1 includes firms with at least one associate and one partner (990 firms).
Sample 2 includes firms with at least two partners (1523 firms).
Sample 3 includes firms with at least two associates (660 firms).
Experience is defined as number of years since the lawyer first passed a bar examination.

Table 2
Sorting Between Partners and Associates By School Tier

PANEL A
COMPOSITION OF ASSOCIATES IN THE AVERAGE PARTNER'S FIRM
BY LAW SCHOOL TIER OF PARTNER

I. Share of Associates of Tier In Row Working With the Average Partner of Tier in Column

			Partner Law School Tier			
		1	**2**	**3**	**4**	**All Tiers**
Associate	**1**	0.16	0.07	0.06	0.05	0.09
Law School	**2**	0.49	0.50	0.39	0.41	0.49
Tier	**3**	0.16	0.15	0.25	0.15	0.17
	4	0.19	0.27	0.29	0.38	0.25

II. Normalized Shares

			Partner Law School Tier		
		1	**2**	**3**	**4**
Associate	**1**	1.70	0.80	0.68	0.56
Law School	**2**	1.02	1.03	0.81	0.85
Tier	**3**	0.95	0.91	1.50	0.90
	4	0.74	1.07	1.15	1.53

Normalized shares equal the shares in the first four columns in the top table divided by the corresponding shares in the fifth.

COMPOSITION OF PARTNERS IN THE AVERAGE ASSOCIATE'S FIRM
BY LAW SCHOOL TIER OF ASSOCIATE

I. Share of Partners of Tier In Row Working With the Average Associate of Tier in Column

		Associate Law School Tier				
		1	**2**	**3**	**4**	**All Tiers**
Partner	**1**	0.23	0.12	0.12	0.07	0.09
Law School	**2**	0.55	0.61	0.51	0.54	0.55
Tier	**3**	0.13	0.13	0.23	0.16	0.15
	4	0.09	0.15	0.15	0.23	0.20

II. Normalized Shares

		Associate Law School Tier			
		1	**2**	**3**	**4**
Partner	**1**	2.51	1.33	1.31	0.80
Law School	**2**	0.99	1.10	0.92	0.97
Tier	**3**	0.85	0.82	1.47	1.07
	4	0.46	0.71	0.71	1.11

Normalized shares equal the shares in the first four columns in the top table divided by the corresponding shares in the fifth.

Table 3
Sorting Between Partners and Associates By Experience

PANEL A
COMPOSITION OF ASSOCIATES IN THE AVERAGE PARTNER'S FIRM
BY EXPERIENCE OF PARTNER

I. Share of Associates of Tier In Row Working With the Average Partner of Tier in Column

		Partner Experience (Years)				
		0-5	**6-10**	**11-15**	**16+**	**All Tiers**
Associate	**0-5**	0.65	0.73	0.70	0.68	0.70
Experience	**6-10**	0.26	0.20	0.23	0.23	0.22
(Years)	**11-15**	0.05	0.04	0.05	0.05	0.04
	16+	0.07	0.03	0.03	0.04	0.03

II. Normalized Shares

		Partner Experience (Years)			
		0-5	**6-10**	**11-15**	**16+**
Associate	**0-5**	0.93	1.04	0.99	0.97
Experience	**6-10**	1.01	0.89	1.01	1.01
(Years)	**11-15**	1.10	0.94	1.05	1.21
	16+	2.43	1.07	1.06	1.41

Normalized shares equal the shares in the first four columns in the top table divided by the corresponding shares in the fifth.

COMPOSITION OF PARTNERS IN THE AVERAGE ASSOCIATE'S FIRM
BY EXPERIENCE OF ASSOCIATE

I. Share of Partners of Tier In Row Working With the Average Associate of Tier in Column

		Associate Experience (Years)				
		0-5	6-10	11-15	16+	All Tiers
Partner	0-5	0.04	0.04	0.03	0.05	0.05
Experience	6-10	0.22	0.19	0.16	0.17	0.21
(Years)	11-15	0.26	0.26	0.24	0.23	0.25
	16+	0.49	0.52	0.57	0.55	0.49

II. Normalized Shares

		Associate Experience (Years)			
		0-5	6-10	11-15	16+
Partner	0-5	0.75	0.67	0.63	0.88
Experience	6-10	1.04	0.91	0.78	0.82
(Years)	11-15	1.02	1.04	0.95	0.92
	16+	1.00	1.06	1.16	1.13

Normalized shares equal the shares in the first four columns in the top table divided by the corresponding shares in the fifth.

Table 4
Sorting Within Partners and Within Associates By Law School Tier

I. Normalized share of partners of tier in row working with the average partner of tier in column

		Partner Law School Tier			
		1	**2**	**3**	**4**
Partner	**1**	2.49			
Law School	**2**	1.02	1.11		
Tier	**3**	0.81	0.81	1.80	
	4	0.59	0.87	0.93	1.49

II. Normalized share of associates of tier in row working with the average associate of tier in column

		Associate Law School Tier			
		1	**2**	**3**	**4**
Associate	**1**	1.99			
Law School	**2**	1.02	1.10		
Tier	**3**	0.92	0.88	1.36	
	4	0.62	0.87	1.02	1.40

Table 5
Sorting Within Partners and Within Associates By Experience

I. Normalized share of partners of experience in row working with the average partner of experience in column

		Partner Experience (Years)			
		0-5	**6-10**	**11-15**	**16+**
Partner	**0-5**	2.40			
Experience	**6-10**	1.02	1.15		
(Years)	**11-15**	0.87	1.00	1.09	
	16+	0.86	0.94	0.98	1.06

II. Normalized share of associates of experience in row working with the average associate of experience in column

		Associate Experience (Years)			
		1	**2**	**3**	**4**
Associate	**1**	1.04			
Experience	**2**	0.94	1.15		
(Years)	**3**	0.86	1.28	1.61	
	4	0.81	1.00	1.44	5.30