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Organizational Attributes and the Distribution of Rewards in a Region: Managerial Firms vs. Knowledge Clusters

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This paper expands the organization theory and evidence on regional industrial agglomerations. We define regional economic activities according to the attributes of the organizations that populate a region and investigate how organizational characteristics influence macro-outcomes at a regional economic level. We focus on two dimensions emerging from two widely known organizational forms: the managerial corporation and the knowledge cluster with a marked orientation toward interfirm knowledge spillovers. We use an original data set of 146 U.S. cities to obtain variations in the extent to which they are populated by managerial firms or knowledge clusters. By utilizing city-level measures of managerial salaries, we test how the intensity of managerial corporation versus knowledge cluster characteristics affects the mean and dispersion of the "rewards" of cities. Our evidence suggests that higher managerial corporate characteristics lower the variability of rewards, while they have no effect on the mean of rewards. Higher-knowledge cluster characteristics produce both higher dispersion and higher expected rewards. We explain these results by looking at the different learning mechanisms of the two organizational types. In so doing, we highlight the role of intra- and interfirm knowledge processes as important sources of differences in the rewards of the two models. From an empirical point of view, results are confirmed using both patent-based and skill mobility—based measures of knowledge spillovers.

Key words: regional cluster; organizational attributes; knowledge spillovers; managerial salaries

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1. Introduction

The nature of the industrial agglomeration processes and their impact on the economic characteristics of the locations in which they take place are critical dimensions of the organization of industries and the competitive advantages of regions (Porter 1998, Saxenian 1994). The literature analyzes industrial agglomerations from the perspectives of social networks (Sorenson 2003), the presence of spontaneous inputs (Chiles et al. 2004), the effects of agglomeration economies (Krugman 1991), or the factors that shape industrial agglomeration as a long-term regional phenomenon, like the work on the identity of clusters by Romanelli and Khessina (2005). The empirical evidence is less extensive. It examines the advantages or disadvantages of firms to locate in a particular region (Kalnins and Chung 2004) or the origin of the externalities in the regional social network (Almeida and Kogut 1999).

Against this background, this paper studies how differences in the organizational attributes of the firms that form an industrial agglomeration generate different regional economic outcomes. We focus on the interrelationships between the distribution of regional rewards

and two archetypal organizational attributes: the managerial corporation and the cluster of companies characterized by interfirm knowledge spillovers.

From a theoretical perspective, we build a framework in which we investigate how the intensity of managerial corporate versus knowledge cluster characteristics influence the shape of the reward distribution of a region. March (1991) notes that the variance and the mean of a reward distribution change according to the underlying organizational learning mechanisms. We specify March's argument by studying the different learning microdynamics of our two organizational attributes, and show that they produce differences in the macrostructure of rewards at the regional level. We develop four hypotheses: holding managerial corporate characteristics constant, an increase in the intensity of knowledge cluster characteristics produce (1) higher dispersion (2) higher mean of regional rewards; holding the region's knowledge cluster characteristics constant, an increase in the intensity of the region's managerial corporate characteristics produce (3) lower dispersion (4) higher mean of regional rewards.

We test these hypotheses by running city-based regressions for a sample of 146 U.S. cities. We employ as dependent variable the salaries paid to managers who reside in the city. Along with controls, we employ proxies for the intensity of managerial corporate and knowledge cluster characteristics. We find that higher managerial corporate characteristics produce less-dispersed regional rewards. However, they do not produce significant differences in the average level of rewards. By contrast, higher-knowledge cluster characteristics imply higher average and dispersion of rewards.

It is important to clarify from the outset of our analysis that managerial corporate and knowledge cluster characteristics are not necessarily substitute. The intensity of the managerial corporate or knowledge cluster characteristics of a region can move—independently—along continuous dimensions. Moreover, managerial corporate and knowledge cluster characteristics are not industry specific. A typical example is the software industry, which features managerial corporations like Microsoft or SAP, along with knowledge clusters in Silicon Valley, Ireland, Israel, India, or Brazil (e.g., Arora and Gambardella 2005). Thus, industry attributes explain only some of the differences in the distribution of rewards, which is why we also need to look at the organizational attributes of the industry in different locations.

In terms of the originality of our contribution, this paper bridges a gap between the established literature on the managerial corporation and knowledge clusters (Audretsch and Feldman 1996, Tallman et al. 2004). Apart from studies like Chesbrough (2000) or Audretsch and Thurik (2001), not much has been done to compare the two. Even the most convincing studies in this area (Saxenian 1994) rely on specific examples. Conversely, we provide a new approach that brings together two streams of literature, and shows how regional reward distributions can differ in both their first and second moment, according to the intensity of the organizational attributes of the firms located within the region.

This is noteworthy for two reasons. First, we expand the organization theory about regional industrial agglomerations by analyzing the issue from a different perspective: from the organizational attributes. In so doing, we also draw attention to an issue that the organizational literature has not investigated in a significant way: differences in the dispersion of rewards, and not just in the expected value. Second, this paper is not centered on the origins of industrial agglomeration (Chiles et al. 2004) or on the type of resources that are developed or exchanged, but on outcomes at the regional economic level. We offer a micro-based foundation centered on a knowledge and organizational argument (Bell and Zaheer 2007, March 1991) to explain some macro differences in regional rewards. We then highlight the role of intra- and interfirm processes of knowledge creation and circulation (Gittelman 2007, Tallman and Phene 2007)

as an important mechanism that explains differences in the distribution of the regional rewards. Note that this explanation does not directly resort to industry-based factors.

Finally, we propose an important contribution at the empirical level. To our knowledge, this is the first article that shows how the measures of knowledge spillovers drawn from patent citations (Jaffe et al. 1993) and from high-skill labor mobility data (Kim and Marschke 2005) produce consistent and similar results.

The next section presents our theory and hypotheses. Section 3 discusses our sample and variables. Section 4 presents our empirical results. Section 5 concludes.

2. Theory and Hypotheses

A taxonomy developed by Romanelli and Khessina (2005) proposes two central organizational attributes to classify regions from an economic point of view: (1) dominance and (2) interrelatedness. They apply these two dimensions to regional clusters. In their framework, regions can exhibit industrial clusters that vary in their size and in the intensity of their interconnections. We go a step further and investigate these two attributes for the firms that populate a region, not within the specific realm of an industrial cluster.

To be precise, we analyze how managerial corporation versus knowledge cluster characteristics affect the dispersion and the mean of regional reward distributions. Organizational attributes affect the learning processes, the interactions among firms, and the knowledge coordination that finally determines the shape of a reward distribution (March 1991). The underpinning of our analysis is that the mean and dispersion of rewards change according to the high-low intensity of managerial corporate or knowledge cluster characteristics. Thus, in our framework they are two dimensions that change along a continuum. This also means that in our setting there are "baseline" regions characterized by firms that are not organized in knowledge clusters—i.e., that do not feature knowledge spillovers—and that exhibit scarce or null managerial-corporate characteristics. As we move along our two dimensions, there will be regions that exhibit more of one of them, more of the other, or more of both, in different combinations.¹

2.1. Knowledge Cluster

The salient feature of the knowledge cluster is the presence of localized interfirm knowledge spillovers. Interfirm knowledge spillovers imply that these firms exploit a common information pool—the classical view suggested by Saxenian (1994). In Silicon Valley, conversely, firms and individuals share common information arising from several factors like alliances, labor mobility, and constant participation in meetings and professional associations. Rivkin (2000) argues that interfirm knowledge spillovers favor imitation among firms, producing

potential similarities in the combination of firm strategies and resources. Powell et al. (1996) show that interfirm knowledge spillovers produced by firms in tight geographical boundaries are correlated with a significant overlap of the firms' final markets. This happens because firms tend to specialize within an industry that shares similar technologies and customers (Romanelli and Khessina 2005). Similarly, on many occasions the main competitors of incumbent firms are geographically bounded spin-offs that inherited competencies in the form of knowledge spillovers (Klepper 2002). Thus, the knowledge cluster dimension stems from the level of interfirm knowledge spillover, firm spatial proximity, common pool of knowledge, rate of imitation, and overlap in the final markets.

The standard perspective about the dispersion of the returns of a set of activities is that the total dispersion is a function of the variances of the individual activities and their combined covariances.² These activities could be innovation projects or, more generally, operational tasks (e.g., project design, prototyping, and definition of manufacturing operations). In knowledge clusters, the first-order effect is on the covariances. With no ex ante coordination, the higher the region's knowledge cluster characteristics, the higher the probability that firms enhance the pursuit of similar activities, increasing the covariances between them, which increases the dispersion of the overall reward distribution.

The increasing dispersion of rewards is reinforced by another consideration that has to do with the variance of the activities. The question whether higher-knowledge cluster characteristics increase or diminish the intensity of rivalry (and so the variance of the individual activities) is still debated in the literature. Strategy scholars from industrial economics (e.g., Caves and Porter 1977) highlight that interfirm imitation and knowledge externalities facilitate tacit coordination and the control of the market, thereby softening the rivalry among firms. By contrast, the resource-based view (Barney 1991) and population ecology (Barnett and Sorenson 2002) suggest that high rates of interfirm mutual learning and imitation increase the intensity of competition among firms. In a related vein, hyper-competition theories (Ilinitch et al. 1996) stress how the threat of imitation triggers firms to adopt a proactive behavior characterized by the need to improve continually their competitive advantages, generating environments that exhibit features closer to winnertakes-all and leader-dethroning models.

As far as our setting is concerned, higher-knowledge cluster characteristics can produce greater congestion of firms in similar markets, which answers the question of how imitation affects rivalry. Gimeno and Woo (1996) triangulate the level of firm rivalry with the degree of overlap of firm markets. They conclude more-intense interfirm knowledge spillovers create *greater* competition when the markets in which the firms compete are

similar. When firms share few similar markets, greater levels of imitation and mutual learning boost competition (Alcácer and Chung 2007). In sum, the more interfirm knowledge spillovers are spatially bounded, the higher the knowledge cluster characteristics, the higher the overlap in the final markets, and the higher the firm rivalry. This implies that higher-knowledge cluster characteristics tend to transform competition into a "right tail" race where only few winners are rewarded handsomely and most of the participants are not rewarded. This leads to a higher dispersion of rewards because the mass of rewards falls onto the right tail of the reward distribution, as opposed to being spread more homogeneously across all the participants in the race.

The right-tail nature of competition implies a stiffer selection in the population of firms and of the underlying competencies. Therefore, differences in the individual abilities that foster productivity gain matter to a greater extent. As a result, when knowledge cluster characteristics are high, the rewards are more likely to reflect natural differences in the distribution of individual skills, expertise, and capabilities. This is also the view suggested by Frank and Cook (1995) who explain disparity in rewards by the presence of "winner-takes-all" markets.3 According to these authors, when organizational success depends almost exclusively on the individual's human capital contributions, the dispersion of the rewards in a market increases, providing a clearer link between the individuals' rewards in a region and the performance of the organizations that populate it. This leads to our first hypothesis.

HYPOTHESIS 1. Other things being equal, environments with higher-knowledge cluster characteristics are associated with a higher dispersion in the reward distribution.

Higher-knowledge cluster characteristics also have a brighter side because firms can use knowledge created by others. Moreover, the firms in knowledge clusters focus on similar information pools and areas, which makes the spillovers more effective due to specialization economies. In high-knowledge cluster environments, activities are not coordinated ex ante: they are only selected ex post by the competitive selection mechanism. As a result, even if they are eventually outcompeted, these activities generate useful knowledge for other firms.

Several authors advance the idea that higher-knowledge cluster characteristics produce an effective mechanism for raising the average performance of firms. Among others, Porter (1998) highlights how firms that are spatially close and share a common knowledge base could achieve a competitive advantage as a cluster. Inspired by Henderson and Clark's (1990) distinction between component and architectural knowledge, Tallman et al. (2004) suggest that higher-knowledge

cluster characteristics regions create *cluster* architectural knowledge that confers a competitive advantage to the firms in the cluster. First, the competitive advantage generates architectural knowledge from the cluster because it has a strong tacit component that is only available to the firms in the cluster. In addition, the higher the knowledge cluster characteristics, the higher the value of the knowledge, given specialization economies, and the more difficult it is to absorb for firms outside the cluster. Similarly, Lampel and Shamsie (2003) coined the term *cluster capability* to mean a pool of shared knowledge resources to which the outsiders of a cluster cannot gain access. According to the resource-based view (Barney 1991), this is a sufficient condition to create a competitive advantage for the firms in the knowledge cluster.

Second, stronger levels of cluster architectural knowledge make the diffusion of component knowledge easier inside the knowledge cluster, generating an additional competitive advantage. This second effect is linked to the reduction of transaction costs. When knowledge cluster characteristics increase, market mechanisms are not necessary, and transaction costs are significantly reduced due to the lack of formal exchanges (Storper 1993).

In sum, the competitive advantage produced by mutual interfirm learning seems to be a common explanation of the superior performance of these knowledge clusters (Audretsch and Feldman 1996) that produce sustainable nonstandard rewards (Sorenson 2003). This leads to our second hypothesis.

Hypothesis 2. Other things being equal, environments with higher-knowledge cluster characteristics are associated with a higher mean in the reward distribution.

2.2. Managerial Corporation

According to the classical Chandlerian-Penrosian view, the managerial corporation is characterized by a division of the organization into subunits focused on specific activities or operations, by a coordination of these subunits and their activities, by hierarchical decision making, and by an ex ante assessment and selection of activities and projects. While the model has evolved since Chandler or Penrose discussed it, these features remain typical.

As discussed earlier, the overall dispersion of rewards has two components: (i) the variance of the individual activities and (ii) their covariances. We hypothesize that higher managerial corporate characteristics produce (i) a lower variance of the returns of each activity, and, for given variances, (ii) a lower combined covariance.

In terms of the variance, the internal division of labor of the managerial corporation hinges on individual specialized expertise performing particular tasks within a set of coordinated activities designed ex ante (Faraj and Sproull 2000). As a result, each human capability is assigned to a particular operational process that is blueprinted in advanced. An increase in the standardization of the processes produces a higher homogenization of expertise that reduces the variability of the final performance. This is the classical effect of routines that makes outcome less variable by creating standard and repetitive assignments (Nelson and Winter 1982). Therefore, the intensity of task standardization and the corresponding homogenization of expertise are responsible for smoothing out individual differences in productivity, and thus the dispersion of rewards.

In addition, there is an extensive literature linking the level of ex ante coordination with the *conservative* behavior of a managerial corporation. This means a "resting on one's laurels" attitude (Christensen 1997), a late-entry strategic choice (Mitchell 1991), path-dependence in learning (Levinthal and March 1993), or cognitive and mental model limitations (Burgelman 1994). Put simply, the higher the level of managerial corporate characteristics, the higher the probability that a firm will select those activities wherein it has better experience and greater abilities to predict the final outcomes.

The other effect comes through the covariance. The coordination inherent in the managerial corporation enables the adoption of a portfolio approach. Given different portfolios of activities with similar total expected return, a coordinated structure tends to pick the portfolios that exhibit low total variance through an appropriate ex ante combination of covariances. If the same activities were conducted by independent organizations, the lack of ex ante coordination would not produce an equally rational choice of covariances. For example, an independent unit will not necessarily reject the development of an activity because there are other potential independent units that will execute some positively correlated activities.

It is worth noting that greater hierarchical coordination produced by higher managerial corporate characteristics can create increasing task dependencies among activities that are, in principle, independent. Therefore, the performance of an individual or unit increasingly depends on the efforts and the performance of several other individuals or units in other organizational layers. Malone et al. (1999) classify the forms of dependence that can be found in a managerial corporation in flow, sharing, and fit. Flow occurs when one activity requires that another activity is performed before or after it; sharing arises when two activities need to use the same resource; and fit happens when they have to match each other by sharing some common protocols. All three forms need coordination. Flow requires scheduling so that the activities proceed in the right sequence. Sharing requires that the firm avoid circumstances that congest the resource when multiple units use it at the same time. Fit requires matching in terms of standards. In this respect, as Malone and Crowston (1994) discuss, when task dependencies generate new correlations among activities leading to a common outcome, greater organizational coordination reduces uncertainty by establishing a temporal sequence of the decisions. Interestingly, this is the same principle developed in game theory, where the multiplicity of Nash equilibria can be reduced by making decisions sequential rather than parallel. Sequential decision making rules out some paths, which may in turn reduce the set of Nash equilibria, and therefore uncertainty. For example, sequential decision making enables the unit that starts a process to pick one of the standard protocols available, to which the subsequent units have to adapt.4 This argument also relates to the standardization of expertise. Increasing division of labor and task dependence imply that the individuals are assigned to activities that depend on and correlate to other modules, and the performance of the overall set of operations depends on how they are entrenched with each other rather than on the particular value of one expertise or activity. In sum, an increasing level of managerial corporate characteristics in a region will reduce the dispersion in the distribution of rewards. Our third hypothesis then reads as follows.

HYPOTHESIS 3. Other things being equal, environments with higher managerial-corporate characteristics are associated with lower dispersion in the reward distribution.

Some inherent characteristics of the managerial corporation can produce efficiency advantages. The impact can be on the benefit side or on the cost side. Efficiency advantages usually translate into a higher mean of the reward distribution (Porter 1998). On the benefit side, increasing coordination and ex ante project selection enable the firm to curtail negative externalities and enhance synergies, for example by avoiding cannibalization across firm products. At the same time, increasing knowledge coordination facilitates the exploitation of synergies or economies of scope across business activities (Zollo and Winter 2002). Indeed, when firms intentionally manage ex ante internal knowledge, scope economies arise and create long-term sustainable advantages. Finally, greater coordination fosters higher specialization and increasing returns in the subunits, as described by Schilling (2000) in the case of organizations that achieve superior quality performance, thanks to the knowledge specialization of hierarchically coordinated subunits.

On the cost side, higher managerial corporate characteristics increase the harmonization of information flows and favor knowledge reusability and the culling of knowledge duplications. This is traditionally a nontrivial source of cost savings (Garud and Kumaraswamy 1993). In addition, coordination and the division of labor inside

the firm, as well as its system of authority, is a powerful source of transaction-cost savings (Jacobides and Winter 2005). Higher managerial corporate characteristics can resolve problems associated with asset specificity or asymmetric information quicker than administrative resolutions by independent third parties (e.g., courts), as in the case of markets.

Another feature of the managerial corporation is that it is more efficient in evaluating its activities. As Sah and Stiglitz (1986) note, organizations can make two types of errors: (1) they can support activities that are eventually unprofitable (Type-I error) or (2) they can reject activities that are eventually profitable (Type-II error). Sah and Stiglitz argue that, in hierarchical organizations, activities are viable only if approved by all the subunits. In a theoretical model, they demonstrate that, other things being equal, hierarchies approve both fewer good and fewer bad projects, i.e., they reduce the probability of Type-I errors and increase the probability of Type-II errors. They then conclude that hierarchies increase or decrease the mean of a reward distribution depending on the underlying shape of the reward distribution. A managerial corporation adds division of labor and knowledge coordination to the standard hierarchy. This means that each subunit checks the particular angle of the activity in which it is specialized and therefore competent. As a result, higher managerial corporate characteristics create assessment capabilities that produce a lower probability to reject a profitable activity (lower Type-II error) and a lower probability to accept an unprofitable activity (lower Type-I error), which is the source of its advantage. This leads to our fourth hypothesis.

HYPOTHESIS 4. Other things being equal, environments with higher managerial corporate characteristics are associated with a higher mean of the reward distribution.

3. Sample and Variables

3.1. Sample

Our empirical analysis employs data on 146 U.S. cities. City-level data are the natural unit of observation to test our hypotheses about the mean and the dispersion of rewards. Basically, we want to compare these measures across *N* units when they operate within one firm or in *N* independent firms. The geographical area is a good candidate for our purposes because there are costs to the geographical mobility of people or units. Cities turn out to be the smallest unit of analysis for which we could find useful and extensive data to address our questions. We therefore assume that there is no significant bias in aggregating firm-level observations for the cities in which they are located.

We select U.S. cities from the locations of the firm headquarters that appear in the Fortune list of the 500

largest U.S. companies and the INC list of 500 U.S. fastest-growing private companies. The rationale for this sampling criterion is to have cities with significant business activities in which there are enough managerial corporations or high growth small-medium firms. We use the two lists only to identify the cities, and we do not utilize the corresponding firm names. We register all the cities in the two lists during three consecutive years: 1998, 1999, and 2000. We then select the first 100 cities in each list after ordering them by their number of firms. There are 249 cities in the Fortune list; the sample of the most important 100 cities accounts for 86% of total sales of all the listed Fortune firms in the three years. There are 486 cities in the INC list; the sample of the most important 100 cities accounts for 75% of total sales of all the listed INC firms in the three years. Because a city could be in both lists, we end up with a total sample of 146 cities. Our sample includes 66% of all the U.S. cities with a population over 150,000. Las Vegas (NV), Honolulu (HI), and Long Beach (CA) are the largest three cities excluded by our sampling criterion since they do not appear as the top 100 cities either in the Fortune list or in the INC list. The sample cities include all the largest U.S. cities (New York, Atlanta, Los Angeles, etc.), along with other smaller cities in which there is significant business activity. For example, our sample distinguishes between Boston and Framingham, a suburb of Boston, where the large office superstore Staples operates.

There might be some concerns about the relationship between cities and firm locations. The problem is not relevant for the many companies that have unique locations, and that exhibit the same legal and operational location. In the case of large multilocation companies, the problem could be more serious. To tackle this issue, we randomly check a sample of large companies with the Mergent Industrial Manual (http://www.mergent.com), which provides data on plants, offices, and other facilities for more than 2,000 top industrial corporations. The address of the firm headquarters corresponds to the presence of quite a few establishments and offices in the city. In addition, our sample includes the city of Wilmington, Delaware. Delaware is a state where many firms maintain small corporate headquarters for tax reasons. We check this city and find that it does not exhibit a particularly large number of firms relative to other cities in our sample. It does not show an apparent bias in some of the other covariates, such as patents. Specifically, in our sample we have only 37 patents in Delaware in the period under study, versus 887 in Boston, 95 in Framingham, 418 in Baltimore, and 1,040 in Philadelphia. The complete list of cities in our sample is available upon request.

3.2. Dependent Variables: Rewards of a Region

Table 1 lists all the variables used in our empirical analysis.

Table 1 Definition of Variables

Variable	Definition
	Dependent variables
Salary	Average annual salary for the Bureau of Labor Statistics (BLS) occupational class "Managerial Occupations" in the metropolitan area (MA), 1998–2000 (in \$). Source: BLS.
Salaryspread	Interquartile range (difference between the 75th and 25th percentiles) of the salary of the occupational class "Managerial Occupations" in the MA, 1998–2000 (in \$). Source: BLS.
Independe	ent variables of theoretical interest
Patentspillover	Share of citations of 1998–2000 patents to other patents granted to unaffiliated entities located in the same city over total citations made by the 1998–2000 patents. Source: NBER Patent Database.
MOBILITYSPILLOVER	Share of scientists and engineers employed in the city who changed employer at least once in the previous year (average 1998–2000). Same variable as in Kim and Marschke (2005). Source: U.S. Current Population Survey.
PATENTCORPORATION	Share of self-citations over total citations made by the 1998–2000 patents. Variable directly computed by the NBER Patent Database. Source: NBER Patent Database.
SIZECORPORATION	Pearson coefficient of skewness (mean minus median over standard deviation) of the employment distribution of the firms in the city, 1998–2000. Source: Osiris Bureau Van Dijk.
	Control variables
FIRMSIZE	Average number of employees of firms in the city, 1998–2000. Source: Osiris Bureau Van Dijk.
SECTOR DUMMIES	Dummies = 1 for trademark sector with largest number of trademarks in the city. Source: U.S. Patents and Trademark Office (USPTO).
HERFINDAHL	Herfindahl index on the city trademarks calculated over the 48 product categories. Source: USPTO.
PATENTGDP	Number of patents over GDP (in million \$) of the MA, 1998–2000. Source: NBER Patent Database, and http://www.epodunk.com.
EDUCATION	Share of population with a four-year degree in 2000. Source: http://www.epodunk.com.
INCOME	Annual income per capita, 1998–2000. Source: http://www.epodunk.com.

As a proxy of the rewards of a city we use the salary of resident managers in the city. Managerial salaries reflect the productivity of the managerial function; they are linked to the performance of the organization. Management is a generalist occupation that can be found in any industry. Therefore, industry composition should not bias this measure of performance. This is also a better measure than standard accounting measures, especially for comparing managerial companies and small-medium firms. Financial databases usually underrepresent small-medium firms, while our U.S. manager salary data, drawn from the BLS, are derived from more than six million individual observations. Salaries, of course, are affected by local market conditions. However, this is functional to our analysis, because the manager salary can be thought of as the opportunity cost of an entrepreneur, and hence can be a measure of the productivity of the entrepreneurial function as well, which is an important dimension of the knowledge cluster.

To be specific, for our sample cities, and for the period 1998-2000, we retrieve the wages of the class "management occupations" from the Occupational Employment Statistics (OES) of the U.S. BLS. This is a fairly wide occupational class that includes many categories of managerial jobs, from CEOs to marketing managers. We assign to each city the 1998–2000 average wage (SALARY) of the U.S. MA where the city is located according to the U.S. MA definition of the U.S. Bureau of Census (http://www.census.gov/population/estimates/ metro-city/99mfips.txt). From the same source, we collect data on the interquartile range of the managerial salaries in the city (difference between the 75th and 25th percentiles). We use the 1998–2000 average of this range as a measure of the variability of the managerial salary (SALARYSPREAD). Among other things, this limits the potential effect of any dot.com fever bias. The dot.com "bubble" occurred during approximately 10 months between June 1999 and March 2000. Thus, we employ a three-year average, with one year before and one year after the bubble.

The BLS definition of wages includes all the elements of the full compensation of the employee foreseen explicitly by the job contract. It then includes individual bonuses mentioned in the contract, but not some collective bonuses offered by the employer on a non-individual basis to all or specific groups of employees (http://www.bls.gov/dolfaq/bls_ques20.htm). Moreover, it includes the stock options explicitly mentioned in the initial job contract, but not those offered outside it.⁵

3.3. Variables of Theoretical Interests

3.3.1. Proxies for Knowledge Cluster Characteristics. Knowledge clusters are characterized by geographically bounded interfirm knowledge spillovers. The empirical literature has measured knowledge spillovers in two ways: (i) patent citations (Jaffe et al. 1993) or (ii) the labor mobility of scientists and engineers (Almeida and Kogut 1999, Kim and Marschke 2005). For robustness reasons, we employ both measures.

We first download all the USPTO patents granted in 1998–2000 in which the address of the assignee is in one

of the cities in our sample. We are aware that the patents of the large multilocation companies may report the address of the headquarters or legal offices even if the research is carried out elsewhere. To tackle this overrepresentation problem, we attribute a patent to a city only if at least one of the inventors' addresses is in the same city of the assignee. This means that if a patent assignee is a firm headquartered in Chicago but no one of the inventors' cities is in Chicago, we do not assign this patent to Chicago. With this criterion, the selected sample covers 67.1% of the entire patent sample. We then match these patents with the NBER U.S. Patent Citation data set (http://www.nber.org). We use the citations made by our sample patents to construct a measure of interfirm knowledge spillovers across firms. This is the ratio (a/b) between (a) the citations made by the patents of firms in the city to other patents by unaffiliated assignees whose address is in the same city, and (b) the total citations of the patents of firms in the city (with the same conservative rule that at least one inventor's address is in the MA of the city). This is a measure of how much city patents rely on patents granted to other organizations in the same city. This variable, which we label PATENTSPILLOVER, is a natural proxy for the importance of current local interfirm knowledge spillovers. To obtain the numerator of PATENTSPILLOVER, we first exclude the citations to firms located outside the assignee's city. Then, from this subsample of patent citations, we exclude the selfcitations (i.e., assignee's citations to its own patents).

Because patent-based measures could be biased (i.e., many industries do not rely on patents to protect innovations; citations are often assigned by patent examiners and not firms), we construct an alternative proxy based on the labor mobility of scientists and engineers. As Saxenian (1994) puts it, people perceive that they are employed "by the Valley" rather than by the individual firms. We adopt the measure employed by Kim and Marschke (2005), since Almeida and Kogut (1999) still use a patent-based proxy of scientist mobility. Thus, from the U.S. Current Population Survey (http://www. census.gov/cps), for the years 1998–2000, and for each city, we calculate the average turnover experience (i.e., the share of mobile scientists) of all scientists and engineers, based on whether they change employers in the year before the survey and whether they remain in the same city. We use the same eight occupation categories for scientists and engineers used by Kim and Marschke (2005). We label this variable MOBILITYSPILLOVER.

3.3.2. Proxies for Managerial Corporate Characteristics. As in the case of knowledge spillovers, we employ for robustness reasons both a patent-based and a nonpatent-based measure to account for the presence of managerial corporations. First, we rely on the fact that in these firms a good deal of the knowledge base and competencies are formed internally. Our theory predicts that the effects on regional rewards are brought

about by the ability to manage and select internal information. To confirm this point, Mowery (1983) observes that the increase in internal R&D raised the importance of intrafirm specific resources of knowledge, especially for large firms. Like in the case of knowledge clusters, we construct a measure of the exchange of internal knowledge from patent data. Thus, our first measure of the importance of managerial corporations is the ratio between the total number of self-citations (i.e., citations to the same assignee) and the total citations made by the patents in the cities. We label this variable PATENT-CORPORATION. A larger value of PATENTCORPORATION denotes that a larger share of the knowledge produced in the city depends on previous knowledge produced within the same organization, as the presence of our archetypal representation of the managerial corporation implies.

We also use a more direct proxy for the presence of managerial corporations, which exploits the fact that these firms tend to be large. For this purpose, from the database Icarus of Bureau Van Dijk, we select all the firms in our sample cities for the period 1998-2000. This produces 10,662 firm-year observations. We then calculate the Pearson coefficient of skewness of the size distribution (measured by the number of employees) of the firms in the city. This is the difference between the mean and the median of the distribution normalized by its standard deviation, and it is an indicator of the skewness of the distribution that does not depend critically on the shape of the distribution itself. A larger value of this variable, which we name SIZECORPORATION, indicates the presence of some very large firms in the city compared to the median firm.

3.4. Variables of Control

We collect control data for each city from several sources. In all the regressions, we use average firm size (FIRMSIZE), sector dummies, city sector specialization (HERFINDAHL), the ratio between the number of patents and the GDP of the city (PATENTGDP), the share of population with a four-year academic degree (EDUCATION), and income per capita (INCOME).

Apart from controlling for the average firm size in the city, FIRMSIZE ensures that SIZECORPORATION captures the skewness of the firm size distribution (i.e., the presence of very large firms) rather than average firm size itself. From the database Icarus of Bureau Van Dijk, we use the average size in terms of employees of all the firms located in the city in the sample period.

Sector dummies control for interindustry differences, and aim at capturing a potential fixed effect of groups of cities, which share the same main business activity. The dummies denote the industry with the largest number of trademarks in the cities among the 48 USPTO trademark product and service categories (NICE classification). Each industry dummy takes the value 1 for all the cities in which the industry is the one with

the highest number of trademarks (e.g., all the cities in which "computers" is the industry with the largest number of trademarks). We end up with 14 sector dummies. For all sample cities, the most important industry accounts (on average) for 32.5% of the entire city trademarks, with a standard deviation of 12.6%. Trademarks are combinations of "words, phrases, symbols, or designs that identify and distinguish the source of the goods (or services)" (USPTO Documentation, http://tess. uspto.gov). We download all the trademarks whose owner's address corresponded to one of our sample cities for the sample period.

To obtain a finer assessment of how many diverse manufacturing activities are present in a city, we use the same trademark source to compute for each city the Herfindahl concentration index among the *shares* of all the city trademarks over the 48 product categories (HERFINDAHL).

The variable PATENTGDP—i.e., the ratio between the number of patents and the GDP of the city—controls for whether the city hosts technologically intensive industries. This is also a way to control for the effect of our patent-citation covariates on the reward measures, because cities with lower patent-intensity could exhibit a lower citation-intensity as well. EDUCATION is the share of population with a four-year academic degree; it controls for the effect of the supply of skills that could influence both the labor market and knowledge spillovers. The income per capita, INCOME, is a measure of the city's wealth and of potential demand factors. We prefer income per capita compared to the housing costs in the city, because there is consolidated empirical literature that treats housing costs as endogenous to income and labor mobility, one of our core covariates (e.g., Bardhan et al. 2003). However, when we use housing costs in lieu of income, our empirical results are largely the same. All three controls above are important to prevent our core independent variables from capturing effects due to the technological intensity, education level, or wealth of the city. These data are from http://www.epodunk.com.

Table 2 provides basic descriptive statistics of the variables used. Table 3 shows the correlation matrix.

4. Empirical Analysis

We test our hypotheses by running robust OLS regressions. Table 4 shows our results by using the two salary-based dependent variables. The baseline model of each set (0) omits the main covariates, showing only the results with the control variables. The other four models of the set (Models I–VIII) use, alternatively, the two proxies for the localized knowledge spillovers (PATENTSPILLOVER and MOBILITYSPILLOVER) and for the presence of managerial corporations (PATENTCORPORATION and SIZECORPORATION), while controls are always included. We use a log-log specification. Because some

Table 2 Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
SALARY	75,473	9,431	53,243	101,114
SALARYSPREAD	54,227	8,280	38,720	74,850
PATENTSPILLOVER	0.091	0.088	0	0.414
Mobilityspillover	0.150	0.018	0.109	0.209
PATENTCORPORATION	0.063	0.063	0	0.304
SIZECORPORATION	0.347	0.150	0.124	0.906
FIRMSIZE	21.864	6.150	11.136	67.956
HERFINDAHL	0.134	0.093	0.023	0.539
PATENTGDP	0.085	0.178	0.001	1.261
EDUCATION	0.239	0.070	0.084	0.377
INCOME	28,190	10,985	12,438	76,668
SECTOR DUMMIES				
Chemicals (dropped)	0.014	0.116	0	1
Cosmetics and cleaning preparations	0.021	0.142	0	1
Pharmaceuticals	0.021	0.142	0	1
Electrical and scientific apparatus	0.582	0.494	0	1
Paper goods and printed matters	0.048	0.214	0	1
Clothing	0.048	0.214	0	1
Toys and sporting goods	0.021	0.142	0	1
Staple foods	0.034	0.182	0	1
Advertising and business	0.034	0.182	0	1
Insurance and financial	0.041	0.199	0	1
Computer, scientific, and legal	0.137	0.345	0	1

variables could take values equal to 0, we use the log of 1 plus the variable.

Both Mobilityspillover and Patentspillover have a positive and significant impact on all our two dependent variables, viz. Salaryspread and Salary. This provides a strong corroboration of Hypotheses 1 and 2. The two covariates Patentcorporation and Sizecorporation have a significant impact on Salaryspread, but they are not significant on Salary. Hypothesis 3 is supported by the data, whereas Hypothesis 4 is not.

Our results about knowledge clusters are the most important and robust findings of this paper. Knowledge clusters induce a premium and a wider dispersion of the rewards. Greater expected rewards in these systems are associated with a greater variability of rewards. Moreover, by using the results in Table 4, we find that, when all the other covariates are held at their mean value, a 20% increase from the mean of either MOBILITYSPILLOVER or PATENTSPILLOVER produces an increase in SALARYSPREAD ranging between 3.7% and 3.9% across our four models. This produces an increase in the difference between the 25th and 75th percentiles of the wage distribution of about \$2,000-\$2,114. The same experiment for SALARY produces a growth in the dependent variable ranging between 2.6% and 2.8% (i.e., \$ 1,962–\$2,113). The concomitant increase in mean and spread is in line with theories that predict that high rates of interfirm spillovers and imitation increase both performance and the intensity of competition among firms. In other words, knowledge clusters increase the productivity of a region, but they also create hypercompetitive environments, which in turn produce a higher spread of returns.

The similarity of the impacts of PATENTSPILLOVER and Mobilityspillover is interesting per se. Thompson (2006) shows that patent citations do not generally measure knowledge flows, apart from the case in which patent citations are local and occur in highly entrepreneurial and innovation-oriented regions. Almeida and Kogut (1999) find that in these regions patent citations are correlated with labor mobility. Thus, as Alcácer and Gittelman (2006, p. 777) conclude, "The mobility of engineers has shown to be a primary mechanism for generating knowledge flows and, by extension, citations across firms." This confirms that local patent citations and the mobility of scientists and engineers are two good proxies for identifying knowledge clusters characterized by local knowledge flows and interfirm knowledge spillovers.

As noted, Hypothesis 3 finds a robust confirmation in our data. Our proxies for managerial corporations (PATENTCORPORATION and SIZECORPORATION) show a

Table 3 Correlation Matrix

1	2	3	4	5	6	7	8	9	10	11
1.000										
0.679	1.000									
0.377	0.367	1.000								
0.372	0.387	0.990	1.000							
0.136	-0.023	0.433	0.424	1.000						
0.106	0.037	0.423	0.417	0.879	1.000					
-0.081	0.053	0.020	0.039	-0.018	-0.038	1.000				
0.355	0.384	0.280	0.293	-0.034	0.037	0.118	1.000			
0.409	0.410	0.355	0.366	0.190	0.306	0.082	0.363	1.000		
0.194	0.230	0.121	0.131	-0.095	-0.011	0.025	0.246	0.333	1.000	
0.333	0.346	0.135	0.130	-0.088	-0.039	-0.003	0.247	0.392	0.749	1.000
	0.679 0.377 0.372 0.136 0.106 -0.081 0.355 0.409 0.194	1.000 0.679 1.000 0.377 0.367 0.372 0.387 0.136 -0.023 0.106 0.037 -0.081 0.053 0.355 0.384 0.409 0.410 0.194 0.230	1.000 0.679	1.000 0.679	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 -0.081 0.053 0.020 0.039 -0.018 0.355 0.384 0.280 0.293 -0.034 0.409 0.410 0.355 0.366 0.190 0.194 0.230 0.121 0.131 -0.095	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 1.000 -0.081 0.053 0.020 0.039 -0.018 -0.038 0.355 0.384 0.280 0.293 -0.034 0.037 0.409 0.410 0.355 0.366 0.190 0.306 0.194 0.230 0.121 0.131 -0.095 -0.011	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 1.000 -0.081 0.053 0.020 0.039 -0.018 -0.038 1.000 0.355 0.384 0.280 0.293 -0.034 0.037 0.118 0.409 0.410 0.355 0.366 0.190 0.306 0.082 0.194 0.230 0.121 0.131 -0.095 -0.011 0.025	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 1.000 -0.081 0.053 0.020 0.039 -0.018 -0.038 1.000 0.355 0.384 0.280 0.293 -0.034 0.037 0.118 1.000 0.409 0.410 0.355 0.366 0.190 0.306 0.082 0.363 0.194 0.230 0.121 0.131 -0.095 -0.011 0.025 0.246	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 1.000 -0.081 0.053 0.020 0.039 -0.018 -0.038 1.000 0.355 0.384 0.280 0.293 -0.034 0.037 0.118 1.000 0.409 0.410 0.355 0.366 0.190 0.306 0.082 0.363 1.000 0.194 0.230 0.121 0.131 -0.095 -0.011 0.025 0.246 0.333	1.000 0.679 1.000 0.377 0.367 1.000 0.372 0.387 0.990 1.000 0.136 -0.023 0.433 0.424 1.000 0.106 0.037 0.423 0.417 0.879 1.000 -0.081 0.053 0.020 0.039 -0.018 -0.038 1.000 0.355 0.384 0.280 0.293 -0.034 0.037 0.118 1.000 0.409 0.410 0.355 0.366 0.190 0.306 0.082 0.363 1.000 0.194 0.230 0.121 0.131 -0.095 -0.011 0.025 0.246 0.333 1.000

Table 4 Robust OLS Regressions

		Dependent variables										
		Salaryspread					Salary					
Models	0.a	I	Ш	III	IV	0.b	V	VI	VII	VIII		
			Hypothesis	1		Hypothesis 2						
PATENTSPILLOVER		0.51** (0.186)		0.47** (0.187)			0.31** (0.134)		0.37** (0.138)			
MOBILITYSPILLOVER			0.54** (0.175)		0.50** (0.175)			0.30** (0.130)		0.36** (0.127)		
			Hypothesis	3		Hypothesis 4						
PATENTCORPORATION		-0.38** (0.170)	-0.39** (0.174)				0.084 (0.184)	0.092 (0.185)				
SIZECORPORATION				-0.044* (0.016)	-0.045* (0.025)				-0.015 (0.024)	-0.013 (0.024)		
		Controls										
FIRMSIZE	0.012 (0.047)	0.003 (0.048)	0.008 (0.040)	0.002 (0.049)	0.002 (0.048)	-0.054 (0.038)	-0.056 (0.039)	-0.057 (0.039)	-0.059 (0.039)	-0.061 (0.039)		
HERFINDAHL	0.05** (0.015)	0.04** (0.016)	0.04** (0.016)	0.04** (0.016)	0.04** (0.016)	0.04** (0.012)	0.03** (0.012)	0.03** (0.012)	0.03** (0.012)	0.03** (0.012)		
PATENTGDP	0.01** (0.008)	0.014* (0.008)	0.014* (0.008)	0.015* (0.008)	0.01** (0.008)	0.01** (0.007)	0.01** (0.007)	0.01** (0.007)	0.01** (0.007)	0.01** (0.007)		
EDUCATION	-0.091 (0.059)	-0.095 (0.058)	-0.097 (0.059)	-0.092 (0.058)	-0.093 (0.058)	-0.073 (0.053)	-0.076 (0.052)	-0.076 (0.052)	-0.075 (0.052)	-0.076 (0.053)		
INCOME	0.13** (0.050)	0.12** (0.052)	0.12** (0.052)	0.12** (0.052)	0.12** (0.052)	0.11** (0.047)	0.11** (0.047)	0.12** (0.047)	0.11** (0.047)	0.11** (0.047)		
SECTOR DUMMIES					Υ	⁄es						
Constant	9.98** (0.433)	9.94** (0.469)	9.93** (0.462)	9.88** (0.462)	9.86** (0.453)	10.7** (0.437)	10.5** (0.425)	10.5** (0.425)	10.5** (0.432)	10.5** (0.433)		
Adjusted R ²	0.243	0.287	0.294	0.281	0.287	0.233	0.260	0.258	0.261	0.259		

Notes. Number of observations 146. p-values based on heteroskedastic consistent standard errors in parentheses. *p-values ≤ 0.10 ; **p-values ≤ 0.05 . All variables are in logs. Variables whose min was equal to 0 were set as log of 1 plus the variable.

negative and significant impact on Salaryspread. This brings empirical support to the view that the structured ex ante control of the internal knowledge of the managerial corporation—involving intrafirm coordination and an effective management of internal information flows—"insures" the environment in which these firms are placed. With all the other covariates at their mean value, a 20% increase from the mean of Patentcorporation and Sizecorporation produces an average decrease in Salaryspread in the models of about 3% and 0.5%, respectively.

By contrast, Hypothesis 4 is not confirmed. Our proxies for the presence of managerial corporations do not produce any significant effect on the mean of regional rewards. It is well known that managerial corporations can also generate bureaucracy costs because they create procedures (for coordination, information flows, project selection, or other operations), or because of the lack of high-powered individual incentives, which is typical of bureaucratic environments. In addition, there are costs associated with the fact that in these organiza-

tions some managers are dedicated to coordination and the resolution of potential conflicts, and therefore cannot be allocated to directly productive activities such as innovation, or the development and launch of new projects and products. In addition, the managerial firm may no longer have an absolute advantage in assessing projects, at least across all sectors. Additionally, external mechanisms, like venture capital or other financial intermediaries, may produce similar project assessment capabilities in decentralized decision-making systems. Our empirical result may then suggest that the classical benefits of the managerial firm in terms of coordination, information flows, and project selection could probably be mediated by other variables like type of knowledge, sector, and financial structure of the production process. This result is consistent with the literature on the relationships between firm size and profitability. A classical contribution is McGahan and Porter (1999), who find that firm size does not affect profitability after controlling for the industry from which the firm originates.

As far as the other covariates are concerned, PATENT-GDP and INCOME tend to be largely significant among the different regressions with a positive sign. This means that richer and more innovation-intensive regions are biased toward a model with higher rewards and higher risks. Herfindahl has a positive and significant sign; it suggests that if a region is concentrated in few industrial activities, then it will produce higher rewards and higher dispersion. This evidence is consistent with our Hypotheses 1 and 2, whereby when there are few and similar markets, knowledge spillovers can generate winner-takes-all models. Firmsize and Education do not produce significant results. Their effects could be shadowed by the other covariates, e.g., PATENTGDP for EDUCATION and sector dummies for Firmsize.

We perform several robustness checks of our results. In particular, we experiment with other specifications of the regressions that we obtain after dropping some of the controls or by using other controls drawn from our data sources—e.g., the unemployment rate of the cities, the population, the average city housing costs, the share of PhDs in the population, the number of firms with more than 1,500, 7,000, or 15,000 employees, or the coefficient of skewness. Because many economic activities involve services, we modify our mobility measure to include financial and consultancy occupations in order to test any potential service-sector bias in our analysis. We also take into account the fact that some of our cities are part of the same Consolidated Metropolitan State Area (CMSA). We run our regressions after introducing two dummies equal to 1 if the city was part of a CMSA that includes three to five or more than five cities in our sample. We find that this categorization marks a distinction between large, medium, and small MAs in the United States. These dummies take into account that for cities in larger CMSAs, there may be factors affecting the dependent variable other than the other covariates in the regressions. As an alternative specification, we introduce the log of the number of cities in the same CMSA in the sample as another covariate. All our results, and particularly the impacts of our variables of theoretical interest, are robust to these alternative specifications. A panel data regression also confirms the results, even if this exercise does not provide any new information, given the scarce time variation of data. We also calculate SALARYSPREAD as the difference between the 10th and 90th Percentile; again, the results are consistent. For brevity, not all these robustness checks are shown. They are available on request.

5. Conclusions

This article expands the organization theory of regional industrial agglomerations (Chiles et al. 2004, Romanelli and Khessina 2005) by discussing the economic effects of different organizational attributes at a regional level.

Our evidence suggests that higher managerial-corporate characteristics produce a lower dispersion of regional rewards, while it has no effect on the expected reward mean of the distribution. Higher-knowledge cluster characteristics produce both higher dispersion and higher expected regional rewards. We explain these results with some fundamental differences in the organizational processes that manage knowledge in these systems (March 1991) and in the related features of their competitive environment.

Our work provides two main contributions. The first is that, although there is a wide literature on the managerial corporation and knowledge clusters, not much has been done to compare the two. We offer one of the first attempts to make this comparison on a systematic basis, from both theoretical and empirical points of view. From an empirical perspective, there is practically no evidence on this matter based on systematic econometric analyses. A notable feature of our analysis is therefore that it hinges on the construction of a detailed and rich data set built from different data sources that have been selected to pick variables specifically suited for our purposes.

Our second contribution stems from the fact that this research trajectory is vital for organization and business studies, because it helps understand an important process in business operations today. As an illustration, in the current literature, there is a great discussion of regional dimensions. We may then have contributed to a better understanding of the links between organizational attributes and regions, and, more generally, we may have encouraged others to think about organizational attributes and regions in a more integrated fashion.

From the theoretical point of view, our analysis makes investors, managers, and policy makers better aware of the implications of these two modes of organizing firms and industries. This means, for instance, that similar policy interventions (e.g., on education, R&D, labor market) could produce different outcomes, in terms of expected returns and dispersion, in the two settings. Our analysis is also consistent with the view that, for investors and private and public venture capitalists, knowledge clusters can generate "gambling-like" situations where a good deal of investment is directed at failing ventures, given the skewed distribution of rewards. As a result, in this environment, where the probability of picking the right investment is lower, the value of cluster information is higher. This may be the reason why most of the venture capital firms, which in the 1970s were financing Silicon Valley ventures from their New York bases, progressively moved or opened subsidiaries in the cluster, or why many venture capital companies were even founded by former Silicon Valley entrepreneurs. Conversely, investments in managerial firms should be intended as insurance benchmarks. Our results also suggest that one can construct balanced investment portfolios on a regional basis, mixing investments in regions characterized by different organizational attributes, instead of the classical industrial or capitalization composition of the portfolio.

Our paper has limitations. The very fact that we deal with new issues—and particularly the comparison between our two organizational attributes-makes our analysis difficult to execute. Compared to more navigated topics, we cannot rely on a good background of previous research. Moreover, new theoretical insights produce new concepts that cannot benefit from readily available data, for example from standard secondary sources. Thus, in spite of the richness and specificity of our data set, for some of our variables the data are not as granular as we would prefer. In particular, manager salaries could underestimate the long-term part of rewards. As a robustness check, we also run the same regressions with a dividend measure as a dependent variable, because dividends could capture a fickle part of the reward distribution that is especially important in case of a widespread adoption of stock-related incentives (Spagnolo 2000). Results are in line with the ones shown in this article. We prefer not to publish them, however, because dividends as they appear in the economic statements are not a perfect proxy of localized rewards, since they could be paid to stockholders throughout the world. In addition, our treatment of the service sector is limited to the robustness check obtained from including financial and consultancy occupations in our mobility measure. Although this addresses the problem in part, there is ample room for obtaining better measures. Finally, our classification criterion for the firm location has inevitable limitations, despite our robustness checks, because it is based on the location of the headquarters.

At the same time, we are comforted by the fact that, in our empirical analysis, we find significant correlations, which suggest that links among our variables exist, and these correlations go largely in the directions suggested by our theory. Moreover, our study is one of the first to employ both a patent-based and a nonpatent-based measure as a proxy for knowledge clusters, and we find that they produce similar results.

Finally, we expect that not only can future research in this area—especially with primary data sources—perfect our theoretical concepts, but it can also employ new measures, showing which variables measure what, and rejecting some measures in favor of others that may be more adequate. For example, it would be interesting to demonstrate how knowledge spillovers intertwine with higher competition for managerial labor in creating higher mean rewards in knowledge clusters. Unfortunately, the lack of granularity of our data prevents us from disentangling effects as specific as this one. We hope that our analysis promotes new attempts to improve upon these issues.

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Endnotes

¹As an alternative to our continuum for managerial corporate and knowledge cluster characteristics, we could think of a two times two matrix with low or high intensity of managerial corporate or knowledge cluster characteristics. Our baseline regions would be in the low-low quadrant, and the positions arising when one or the other dimensions, or both, increase are straightforward. The key elements of our discussion in this theory section would not change.

²Suppose that each activity generates some performance that can be quantified as x_i , where $i=1,2,\ldots,m$. Each return x_i has an expected value μ_i and a standard deviation σ_i . If the total return from all the activities is a linear combination of the single activities, viz. $X = \sum_{i=1}^m \omega_i x_i$, where the weights $\omega_i \in [0,1]$ sum up to 1, then the variance of X, i.e., Var(X), is the weighted sum of the individual variances plus two times the cross-covariances multiplied by the corresponding weights, i.e., $Var(X) = \sum_{i=1}^m \omega_i \sigma_i^2 + 2 \sum_{i=1}^m \sum_{j \neq i} \omega_i \omega_j Cov(x_i, x_j)$.

³A winner-takes-all environment may imply a negative ex post covariance in the expression for Var(X) (see Endnote 2). First, however, the corresponding increase in the variance of the x_i may offset this negative effect. In addition, the common shock that we hypothesized in the knowledge clusters (the ex ante covariance, p. 3) may counterbalance this winner-takes-all effect

⁴A simple way of thinking about how coordination reduces uncertainty in this case is to consider two units that produce two resources that have to fit by using the same standard. Suppose there are two standards, A and B. Independent decision makers in the market would not know if the other uses A or B, and this adds uncertainty because, given the standard chosen by either of the two units, there is only a 50% chance that the other will match. In the managerial firm, a higher-level manager would define ex ante the standard to be followed, which removes the uncertainty about the standard that the other units will adopt. Equal examples could be made for "flows" (when two events need to start in a given sequence, and the units have to coordinate on when to start) or "sharing" (when two units have to use the same resource and they have to coordinate on when to use it).

⁵Thus, we acknowledge that manager salaries could underrepresent the long-term components of manager compensation like bonuses, share awards, health care, and retirement benefits. In short, the salary-based measures may not include part of the long-term payment, especially when manager salaries are linked to *ad hoc* share option compensations.

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