The organization of R&D within firms: Measures, characteristics and consequences*

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Abstract

We explore the relationship between firms' R&D organization and performance. Both the information-processing view and the incentives-based view of firm organization imply that centralized R&D will be more scientific, broader in scope, and have more technical impact, while being more likely in firms that operate with a narrower range of businesses or in complex technologies, and are more reliant upon acquisitions. Empirically, we develop a novel dataset on the organizational structure of 1,290 American publicly-listed corporations, 2,615 of their affiliate firms, as well as characteristics of 594,903 patents that they hold. By using intra-firm patent assignments to affiliates as a proxy, we measure the level of firm-level R&D decentralization, and generally find support for our propositions. Additionally, we find strong results for impact on outcomes that are not clearly predicted by current theories: firms that decentralize R&D invest less in R&D and produce fewer patents, while exhibiting greater sales growth and higher market value. We discuss possible explanations for these findings.

Keywords: decentralization, patent assignment, market value, R&D

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1 Introduction

Our understanding of how organizations function has advanced substantially in the decades since Coase, Simon and Williamson began to investigate the determinants of organizational arrangements. And yet due to the difficulty of looking inside the black box of the firm, many debates pertaining to the internal organization of firms (including why firms centralize or decentralize, which is our present subject) remain unresolved. In this paper we advance this exploration by analyzing new data on the assignment of patent rights within large American firms, using the decision to assign patents either to headquarters or to affiliates as a proxy for the level of de facto decentralization of R&D in a firm. We shall discuss the strengths and weaknesses of our measure in section 2. We recognize that it is plausible, and even likely, that our measure captures centralization or decentralization of other types of authority in the firm as well (such as management of intellectual property, and licensing), not merely that of R&D. Nonetheless, we shall largely speak of R&D, mostly for sharpness in exposition.

There are a variety of theoretical perspectives, and a wealth of historical experience, on the determinants and implications of centralizing R&D activities. As we discuss below, neither theory nor historical experience suggests that one organizational form would dominate the other, and this is not the focus of paper either. Instead, our objective is to provide a systematic empirical examination of the phenomenon, both useful in itself, and to inform further theory development. In this paper, we document (a) the characteristics of the research under different organizational forms, and (b) the implications of the different forms for outcomes such as R&D investment, patenting, growth and market value.

Our paper combines data from several sources: (i) patent level information from the United States Patent and Trademark Office (USPTO), (ii) ownership structure data from Icarus and Amadeus by Bureau Van Dyke, (iii) Merger and acquisition data from Thomson Reuters SDC Platinum and Zephyr by Bureau Van Dyke, and (iv) accounting information from U.S. Compustat. Our sample includes 594,903 patents that are matched to 1,290 American publicly-listed corporations, a total of 30,834 of their private and public affiliates, of which 2,615 were assigned at least one patent. We matched a total of 594,903 patents to our firm sample, where 107,654 of these patents (18.1%) are assigned to affiliates.

Though a vast literature deals with the decentralization of tasks and authority in organizations, the majority of this work tents to be theoretical (see Mookherjee 2004 for a review of the economics literature), and empirical studies remain scarce. Most of the empirical studies focus on the impact of changes in communication costs or the adoption of information technology. For example, using US data, Rajan and Wulf (2005) provide empirical evidence that firms tend to select flatter organizational structures in more recent years relative to the past. Bresnahan, Brynjolfsson and Hitt (2002) and Caroli and Van Reenen (2001) find that with greater investment in information technology, firms tend to adopt more decentralized organizational structures. Acemoglu, Aghion, Lelarge, Van Reenan and Zilibotti (2007) show that for Britsh and French manufacturing firms in the 1990s, those closer to the technological frontier, operating in more heterogeneous environments, or younger, are more likely to decentralize. Colombo and Delmastro (2004) find that local information increases decentralization to plant managers in Italian firms, as does superior communication technology, but centralization increases with the need for coordination. Bloom, Sadun, and Van Reenen (2008) study decentralization to local plant managers in a large sample and find that trust and social norms increase decentralization as does product market competition (which proxies for importance of local information). Hubbard (2003) shows that the use of on-board computers in trucking improved coordination between dispatchers and drivers, and increased productivity.

This empirical research is motivated by a variety of theoretical perspectives, which can be broadly classified into two major ones: information processing, and incentive based. A standard approach to decentralization posits the existence of differences in information between levels of the firm (e.g., Radner and Jacob Marschak 1972). In our context, an affiliate (which we use loosely to include divisions and business units) may have more information than headquarters about which research projects are worth pursuing, which inventions are worth patenting, which patents are worth maintaining and enforcing, and which licensing deals are worthwhile. Superior information implies that the affiliate can make better decisions. However, though better informed about its own needs, the affiliate may be ill-informed about those other parts of the firm. Thus, leaving the affiliate with the authority over these decisions has to be balanced against other considerations. In the information processing view, the principal one is the cost and time involved in communicating the relevant information up the hierarchy, needed for coordinating the actions of the various affiliates. If communicating this information to headquarters in full detail is costly or otherwise not possible, this literature (e.g., Radner and Jacob Marschak, 1972) has argued that splitting tasks by means of a hierarchy can be useful to minimize delay (Radner 1993; Van Zandt, 1999), facilitate specialization (Bolton and Dewatripont, 1994), or both (Patacconi, 2009).

The incentives based perspective, in which we include both transaction costs (e.g., Williamson, 1975) and the principal-agent theory, has identified a second set of tradeoffs. Delegating authority to the affiliate raises the possibility that the affiliate, though having superior information, may still take inefficient decisions because its interests are not fully aligned with those of the firm as a whole. Managers in the affiliate may fear being "held-up" by top management, and thus under-invest. Decentralization is a means of credibly assuring them against such expropriation. For instance, Riordan (1990) provides a model in which a principal delegates authority to provide incentives for cost reduction. Aghion and Tirole (1997) provide a model in which a principal delegates authority as a credible way of leaving information rents with the agent, so as to provide incentives for suitable choice of projects. Credible delegation of authority can be optimal because it promotes high-powered incentives to managers in the form of contracting on observable outcomes, or by managing strategic communication of information, which may be costless but possibly biased (Dessein 2002; Alonso, Dessein and Matoushek, 2008). Similarly, Belenzon, Berkovitz and Bolton (2009) argue that affiliates in business groups have superior incentives to invest in more basic innovation because they enjoy greater legal protection against the "parent" firm expropriating their rents from innovation. Of course, as clear in Baker and Hubbard (2003), and Dessein, Garicano, and Gertner, (2009), incentive alignment and coordination problems also interact. Indeed, there is a vast literature in economics on this topic, and the reader is referred to Mookherjee (2004) for a review.

Scholars have emphasized other incentive-related channels through which decentralization may affect behavior. Most notably decentralization is arguably associated with higher flexibility (Child, 1984, Mintzberg, 1979), independence (Kanter, 1985), initiative (Chandler, 1977), or merely through the motivation arising from the perception of freedom (Gupta and Govindarajan, 2000) or pride of ownership (Estrin et al. 1987), which may stem from being associated with the generation of inventions. This is especially interesting as a counterpoint to the well documented "not invented here" (NIH) syndrome , e.g.

(Rotemberg and Saloner, 1994, Szulanski 2009; Teece 1996) that has plagued many firms post-merger, where divisions are reluctant to embrace ideas coming from other parts of the organization.

The specific focus of this paper—on the decentralization of innovation activities—builds upon Argyris and Silverman (2006), and Kastl, Martimort and Piccolo (2009). Kastl et al. (2009) frame their study in terms of whether decentralization – delegation of authority regarding R&D as well as financial, administrative and business decisions to divisions and affiliates – provides superior incentives for investment in R&D. They find that decentralization is associated with greater investments in R&D in Italian manufacturing firms. They also explore the determinants of decentralization and find, contrary to Acemoglu et al. (2007), that age, distance to the technology frontier, and heterogeneity of the environment are not associated with decentralization. Argyris and Silverman (2006) study the organization of R&D in a sample of 71 large US corporations. Unlike Kastl et al. (2007), they focus specifically on the organization of R&D, rather than the organization of the firm more broadly. Building on both the information processing perspective and the incentive perspective, they hypothesize and find that decentralized R&D results in lower impact research outcomes, and with research that is narrower in technical and organizational scope.

We contribute to this research in a number of ways. First, unlike Kastl et al. (2009) and Arygris and Silverman (2006), we do not use survey based measures of decentralization. Instead, we use observed behavior (i.e., whether patents are assigned to the parent entity or decentralized to divisions) as a measure of the extent of decentralization. Patent data are widely available and our study opens the possibility for further research using patent assignments in this manner. Unlike Kastl et al. (2009), whose sample is mostly small Italian manufacturing firms, our sample consists of nearly 1500 large, publicly traded, US firms. Our sample, though similar to Argyris and Silverman (2006) is considerably larger, and we can also explore the determinants of decentralization, as well as it consequences. Thus, we study not only the nature of R&D, as Argyris and Silverman (2006) do, and the amount of R&D, as in Kastl et al. (2009) do, we also study how decentralization is related to patenting behavior itself (i.e., we estimate a patent production function). Moreover, we also study how the extent of decentralization is related to other outcomes such as sales growth and the market value of the intellectual assets of the firm.

We find that decentralization is more likely for firms that operate in discrete technology industries, have a greater focus on incremental R&D, rely more heavily on acquisitions, and that manage a diverse range of technologies. We also find that centralization is associated with greater emphasis on science. Further, decentralized firms tend to invest less in R&D, generate fewer patents from their R&D, but also grow faster. Intriguingly, we also find that decentralization explains a substantial portion of the variation in the market value of the firms in our sample.

The rest of the paper is organized as follows: In Section 2 we discusses the various issues associated with using patent assignments to measure the extent of decentralization of R&D. Section 3 discusses the contrasting implications of centralizing versus decentralized R&D in multidivisional firms. Section 4 describes the data and our measures, and discusses some strengths and weaknesses. Section 5 presents our empirical findings on how decentralization is related to the nature of the firm's environment, and the nature of its research. Section 6 explores the relationship between decentralization and outcomes. Section 7 concludes by summarizing our findings and discussing the implications for theory and practice.

2 Patent assignment and decentralization

2.1 Patent assignment as a measure of R&D decentralization

Our principal measure of the extent of decentralization is the share of patents that are assigned to wholly-owned American affiliates. This measure has the advantage that it is based on observed behavior, can be used for large samples, and it can be easily replicated in other settings, because it is not based on ad hoc surveys. Its use as a measure of decentralization of R&D raises several issues.

It is possible that a business or division inside a firm have de-facto authority over its R&D and innovation, but because it is not a distinct legal entity, does not have patents assigned to it. In other words, roughly speaking, decentralization of patents is a sufficient, but not necessary condition. Even so, the very fact that an affiliate is a distinct entity, rather than merely a division of the parent, is significant. Frequently, when a business is acquired, the acquirer faces the choice of dissolving the acquired entity and integrating it, or letting it remain distinct. The assignment of patents is a signal, therefore, that the acquired business enjoys a significant measure of autonomy, including the freedom to direct its R&D. For example, Genentech, though wholly-owned by Hoffman La Roche, directly contracts on licensing the patents in its charge to outside firms. This ability to independently write contracts may have incentives implications not found where all contracts are centrally underwritten. Assignment may also reinforce the identification and long-term ties between a manager and the patents she manages, so that opportunistic behavior costly in terms of reputation (Gibbons, et al., 1999; Alonso and Matoushek, 2007). Some of these themes repeatedly occurred in our interviews with managers from sample firms.

A second issue is that patent assignments may reflect decentralization of authority more broadly, rather than merely R&D. In this sense, our measure could pick up not simply R&D decentralization but also decentralization of other types of functional authority. We readily acknowledge this. Note that by construction we only observe patent assigned to affiliates if the affiliates are distinct legal entities, albeit wholly owned entities. This implies that our measure of decentralization is likely an under-estimate of the true extent of decentralization. Although this is not classical measurement error, it is likely that the estimated coefficients suffer from attenuation bias. That is, we are likely underestimating the association between decentralization and various other economic outcomes of interest.

Conversely, one might suspect that patent assignments reflect much narrower decentralization – instead of reflecting decentralization of R&D, we are merely observing the decentralization of IP management. Patent assignments can be driven by tax avoidance strategies. This is particularly salient in international settings, which do not apply in our context. However it is also featured in some of the cases in our sample, where all patents are assigned to a wholly owned subsidiary that is located in states that do not tax royalty incomes. We conservatively classify all such instances as if the patents were assigned to the parent firm. Patent assignment may also be driven by a desire to have patents assigned in the name of the relevant business to make it easier to assert patents, obtain injunctions, and receive adequate damages. However, this concern only arises if the business in question is a distinct legal entity rather than a division of the parent firm, suggesting decentralization.

A different interpretation, which also supports the delegation of authority interpretation, is that affiliates which may be potentially divested in the future are also likely to enjoy greater autonomy, including autonomy in managing their intellectual property. For instance, when Motorola divested its semiconductors manufacturing business (now called Freescale Semiconductors), there was considerable delay in sorting out which Motorola patents were going to be assigned to the divested business. This example, which emerged in one of our interviews, suggests that patent assignments are a plausible signal that the affiliate has a certain "hands-off" relationship with the parent.

There are some other potential concerns, which, however, do not appear to be as salient in our context. First, contrary to our assertion, it is possible that an affiliate may receive patent assignments without enjoying the hypothesized autonomy. Our interviews suggested the contrary. Second, patent assignments may simply reflect corporate inertia, with no implications for the allocation of decision making authority or autonomy. We can rule this out. We systematically investigate patent reassignments. Reassignment of patents signal intent – firms have to incur cost and effort to reassign patents. It is reassuring that the vast bulk of reassignments are from headquarters to affiliates, indicating that at the very least, our measure of decentralization reflects intent rather than mere inertia.

On balance, we believe that patent assignment to affiliate are a signal, albeit perhaps a noisy signal, that the affiliate enjoys autonomy regarding R&D decisions, as well as perhaps other types of business decisions.

2.2 Organization of R&D within multidivisional firms

The tension between centralization and decentralization of R&D in American corporations has persisted for several decades. Hounshell and Smith's classical study of R&D in Du Pont highlights these tensions, which are reflected in the shift between decentralization and centralization. Du Pont's pre-WWI diversification efforts created a situation where the centralized R&D was deemed as insufficiently responsive to the needs of a diverse set of businesses which included explosives, celluloid plastics and films, lacquers, paints and varnishes, and dyestuffs. Consequently, during the 1920s, the individual businesses were given authority over their R&D activities, with each business creating a separate research division to serve its needs. Under Charles Stine, centralized R&D gradually grew and regained prominence by 1928. Centralization grew partly because the various businesses were still connected by a common scientific base, so that a new type of nitrocellulose based lacquer finish, Duco, was invented by the cellulose division instead of the paints and varnish division. Duco proved to be a major success, and highlighted the problems with decentralized R&D – R&D often had spillovers, and thus, decentralized R&D required extensive coordination. For instance, using Duco for furniture required additional technical advances in resins, which were carried out by the Chemical Department, as Du Pont's central R&D organization was called. Interestingly, Du Pont patented these inventions and forced other paint manufacturers to take licenses. Hounshell and Smith (1988: 146) report that Duco royalties amounted to more than $10 million, compared to the $750,000 that Du Pont had invested in developing it.

Centralization of R&D was also helped by the need of successful businesses, such as Rayon, for growth opportunities. However, researchers in the rayon division were constrained to work on cellulosic fibers (of which Rayon is an instance). The true opportunities, however, were in synthetic fibers. The general manager of the Rayon division was reluctant to authorize more broad ranging research. As one R&D manager noted in 1933 "In our some ten years rayon experience, we have in but two cases bent any part of our research program in a direction other than one relating directly to the most immediate manufacturing and selling problems ... Unless we conclude that there will be no radical departures in the synthetic fiber (or film) industry in the next ten years, then it must be concluded that our technical program falls short in its more radical and forward looking aspects". (Hounshell and Smith, 1988: 181-182). The point, as Argyris and Silverman stress, is that decentralized R&D tends to be product focused. Central R&D organizations are both better able and better motivated to invest in more basic, non-specific R&D. Sometimes, this type of research yields huge payoffs, as Charles Stine's investment in polymer R&D did, when it yielded both neoprene (a synthetic rubber) and nylon.

The scientific and commercial success of Nylon is well known. Less appreciated, perhaps, is the impact on the organization of R&D. Simply put, it provided the justification for a major investment in basic research in Du Pont, almost exclusively conducted by the Chemical Department under Charles Stine. Although this research yielded a number of other major technical advances and contributed to the development of major new products such as polyethylene and polyester, it also led to a focus on science and on basic research. Indeed, the new laboratory for fundamental research was dubbed "Purity Hall" by Du Pont chemists, signifying its distance from the grubbier concerns of the businesses. This is another feature of centralized research. Along with a focus on non-specific research, centralized R&D also tends to be more scientific in its orientation.

The same tension is also illustrated in a different case, half a century later, in a different technology and company, IBM. IBM scientists made fundamental contributions to the development of relational databases, which help store and retrieve electronic data efficiently. Yet, it was only when a startup, Software Development Laboratories headed by Larry Ellison, that would later become Oracle Corporation commercially introduced a relational database that the IBM database division took notice of the technology. This example, which is far from the only one of its kind, illustrates the tension. Relational databases depended on research which was carried out in a central R&D lab, with a strong basic research orientation. It is unlikely that it would have been developed in a more product oriented divisional R&D lab. Indeed, recent evidence suggests that Software Development Laboratories relied upon the technical disclosures on relational databases by IBM (Bhaskarabhatla, 2010).

These examples show both the power of centralization and the potential drawbacks. The information processing perspective suggests that decentralized R&D will exploit local information more effectively, and that its results will be exploited more readily. The incentive perspective suggests that decentralized R&D will be more responsive to the needs of the division or affiliate that sponsors the research. In sum, decentralized research will also be better aligned with the immediate needs of the affiliate. However, this research is less likely to "spillover" to other divisions, both by its narrower scope and because the affiliate would have limited incentives to invest in research that could spillover to other parts of the firm. Indeed, the competition for resources inside the firm may create incentives against such research, lest it allow other divisions to use the fruits of the research and claim additional resources, as was apparently the case with Duco and the Cellulose Division in Du Pont. In contrast, centralized R&D is more conducive to more pioneering research, research that explores new markets, and more fundamental advances. As the examples suggest, it is also more susceptible to "capture" by a scientific and technical elite, whose interests may extend well beyond those of the firm, and who may see their mission as advancing the technical and scientific frontier as much as maximizing the profits of their firm.

Furthermore, centralization of R&D also facilitates greater coordination across the various affiliates. This coordination is more valuable when the affiliates share common technologies (i.e., are more closely related) or if the products (of the various affiliates) themselves must be mutually compatible or have other forms of inter-dependencies. Put differently, centralization of R&D is more likely to be observed when the firm operates a narrow ranges of businesses, or if the underlying technology is "complex", with marketable products being composed of many different parts, often produced by distinct businesses (see Cohen et al.). Conversely, a diverse range of businesses and "discrete" technology would favor decentralization.

A key source of variation across firms in our data related to decentralization is mergers and acquisitions. Firms differ both in the extent to which they acquire other businesses, and how they deal with such acquisitions. Centralization is obviously easier to manage if acquisitions are relatively rare, because each acquisition would then require integration of new research teams and organizations. Conversely, decentralized firms would naturally find it easier to deal with acquisitions. Finally, mergers, acquisitions and divestitures are a fact of life. Anticipating our empirical analysis, we control for acquisitions and its effects in a couple of ways that are detailed below.

Following conventional practice in the management and strategy literature, we restate the above as hypotheses, although we hasten to add that the incentive perspective is rich enough to allow one to develop scenarios that generate different implications. For instance, Belenzon et al. (2009) provide a theoretical model in which broad decentralization of authority to affiliates is a credible means of reassuring managers of the affiliate against interference and expropriation by the parent, inducing them to invest in more basic and long term research. In this model, decentralization would be associated with more rather than less basic research.

Hypothesis 1. Centralized R&D will be more scientific in orientation, broader in scope, and have more technical impact. Conversely, decentralized R&D will be less scientific, narrower in scope, and incremental in technical terms.

Hypothesis 2. Centralized R&D is more likely to be observed in firms operating in a narrow range of businesses, in complex technologies. Centralized R&D is less likely in firms that actively acquire external businesses.

2.3 Organization of R&D and outcomes

Theoretical perspectives provide less pointed guidance on how the different organizational forms are associated with outcomes. Consider for instance the implications for the extent of investment in R&D. Here, the information processing perspective is largely agnostic; local information may imply more or fewer opportunities for R&D. Further, although centralization might eliminate duplicative research (implying lower R&D), it may also identify fruitful avenues for research (implying greater R&D). On the other hand, centralization may allow a more efficient internalization of spillovers, which would imply that centralization should be associated with greater R&D. The incentive perspective broadly suggests that an affiliate with greater autonomy would be able to appropriate more of the benefits from its R&D investment, implying that decentralization should be associated with greater investments in R&D. Insofar as centralized R&D is associated with greater power researchers in the firm, these researchers may be able to capture more resources, reflected in bigger R&D budgets.

It is not merely the amount of R&D but also the effectiveness of R&D which is implicated in how innovation is organized. The information processing view would suggest that decentralized R&D should be more useful for advancing existing businesses but less so in creating new ones, the ability to internalize spillovers should make centralized R&D more productive. The incentive approach would suggest that the ability to appropriate returns would lead to the choice of more productive R&D projects, implying that decentralized research should be more productive.. However, the researcher-capture view would indicate that centralized R&D would be less productive.

Given the mixed nature of the findings, it seems prudent not to advance hypotheses; instead, we treat this an empirical matter.

3 Data and measures

Our paper combines data from several sources: (i) patent level information from the United States Patent and Trademark Office (USPTO), (ii) ownership structure data from Icarus and Amadeus by Bureau Van Dyke (BVD), (iii) Merger and acquisition data from Thomson Reuters SDC Platinum and Zephyr by Bureau Van Dyke, and (iv) accounting information from U.S. Compustat. The Appendix details the procedures used to construct the various datasets that comprise our platform.

Parent firms and affiliates. Ownership data consists of two parts: cross-sectional ownership information from Icarus and Amadeus for 2008, and M&A data from SDC Platinum and Zephyr. The cross-sectional data informs us on existing active affiliates, and the M&A data tell us whether acquired entities have remained independent, been dissolved, or have been fully integrated into the parent company. Our final sample includes 1,290 American publicly-listed corporations. We distinguish active versus "dormant" affiliates - wholly owned subsidiaries with no significant economic activity that exist mainly for tax purposes, as well as affiliates that are established solely as holding vehicles for the purpose of IP management. This screening leaves us with a total of 30,834 affiliates, of which 2,615 are assigned at least one patent during our sample period.

Patents. Patent data are from the USPTO for the period 1975-2007. We match all granted patents to our sample of firms and affiliates. It is important to stress that we allocate patents to parent companies only if the parent is the listed assignee. Thus we distinguish between centrally assigned patents - patents that are directly assigned to the parent company, and decentralized patents - patents that are assigned to affiliates. We matched a total of 594,903 patents to our final sample of Compustat firms. 107,654 of these patents (18.1%) are assigned to affiliates. Patents assigned to non-active affiliates are classified as if assigned to the parent.

Figures 1 and 2 show how different the observed patent-assignment behavior of firms can be. Abbott Laboratories and Johnson & Johnson are similar in many ways. Both firms are heavy patentors, operate in similar industries (pharmaceuticals and medical devices) and have historically engaged in numerous acquisitions. However, Abbott assigns 67% of patents centrally, and we see very few patents assigned to Abbott affiliates. On the other hand, Johnson & Johnson shows a scant 8% of centralized patents, and has several affiliates with a higher share of patents than itself.

Insert Figures 1 and 2 here

Scientific Publications. Our second measure of innovation are publications in academic journals. We develop systematic data on firm publications to proxy for science-based inventive activity by firms. [1] 289 corporations in our sample publish at least one scientific publication. Top publishing firms include IBM (27,879 publications), Merck (14,585 publications), Pfizer (7,595 publications), Eli Lilly (7,574 publications), HP (6,874 publications), and Lockheed Martin (5,482 publications).

Reassignments. We are interested in two reassignment types: (i) reassignments from parent to affiliates, and (ii) from affiliate to parent. [2] Reassignment data is taken directly from the USPTO website (using a specialized "spider" program), and then merged to our final patent sample. To determine reassignment type we match old and new assignees to our firm name sample. Ultimately, 41,244 patents in our sample are reassigned. Close to 90% of these reassignments are assigning a patent from parent to an affiliate (36,180 patents).

Accounting and financial data. Accounting data are from U.S. Compustat. We match our firms using a string name process similar to the one we utilize to match patents to our ownership structure data. The book value of capital is the net stock of property, plant and equipment; Employment is the number of employees. R&D is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate (Hall, Jaffe and Trajtenberg, 2005). So the R&D stock, GRD, in year t is $GRD_t = R_t + (1 - \delta)GRD_{t-1}$ where R_t is the R&D expenditure in year t and $\delta = 0.15$. Patents stock, $GPat_t$, is calculated in an analogous way. Patents stock in year t is $GPat_t = P_t + (1 - \delta)GPat_{t-1}$ where P_t is the citations-weights flow of patents in year t. To control for patent quality we weight each patent by the ratio between the number of citations it receives and one plus the average number of citations received by all patents that were granted in the same year. Firm value is the sum of the values of common stock, preferred stock and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles other than R&D. Tobin's Q (market value over capital) was winsorized by setting it to 0.1 for values below

[1] We match all firms in our sample to the Thomson's ISI Web of Knowledge database, which includes publication records on thousands of international scientific journals. Belenzon and Patacconi (2010) provide detail on the matching procedure

[2] For example, we find evidence of the first type of reassignment in many patents held by Boston Scientific, which were assigned to affiliates such as Advanced Bionics and Sci Med Life Systems years after Boston Scientific bought them. As well, we see patents going from acquired affiliate to headquarters, for example Matrix Semiconductor assigning 157 of its 421 patents to parent company Sandisk. A third type of reassignment is inter-firm. Because the current paper deals with intra-firm allocation of IP rights, we exclude inter-firm reassignment from our sample.

0.1 and at 20 for values above 20.

Tables 1 and 2 provide summary statistics on our firm sample. Our sample's average firm is valued at \$1.4 billion, has \$3.6 billion in sales, \$488 million in R&D stock, and holds a stock of 132 cites-weighted patents. Our main variable of interest is the share of decentralized patents stock. That is, the share of patents that are assigned to affiliates, and not headquarters. On average, the ratio of decentralized patents across firms is 36%. Using the patent as the unit of analysis, 18.1% of patents are assigned to affiliates (as we shall see later, firms that patent a lot are less likely to assign patents to affiliates, which explains the difference between patent and firm-level assignment). The average patent receives 8.9 (or 11.3 when restricting the sample to patents that receive at least one citation).

Table 2 reports the raw correlations between our main variables of interest. Share decentralized is strongly correlated with the firm share of acquired patents of it total patents. Share decentralized is positively correlated with Tobin's Q (the ratio between market value and assets) and sales, and is negatively correlated with patents and R&D stocks and flows. We next proceed to an econometric investigation of these relationships.

Insert Tables 1 and 2 here

4 Econometric results

4.1 The nature of decentralized research

We estimate the following specification to explore the nature of decentralized research:

$$\Pr(Affiliate_i) = \Phi(\beta_1 \ln Cites_i + \beta_2 Basic_i + \tau_t + \eta_j + \mu_k) \tag{1}$$

Where $Affiliate_i$ is a dummy that receives the value of 1 for patents that are assigned to affiliates (rather than headquarters). $Cites$ is the total number of citations a patent receives, Basic denotes patent characteristics that we associate with basic inventions (described in more detail below), τ_t denote the patent grant year, η_j denotes the patent main technology area, and μ_k is the firm. If decentralized patents are, on average, of lower quality and more incremental (less basic), we expect $\widehat{\beta}_1 < 0$ and $\widehat{\beta}_2 < 0$.

Table 3 reports the estimation results (marginal effects of a Probit model). Here the general pattern of results is consistent with our *Hypothesis 2,* which predicts that centralized R&D will be more likely to be observed in firms operating in a narrow range of business, in complex technologies. First, there is a strong positive relationship between discrete technologies and decentralization. We classify our sample patents to 7 main technology areas based on their International Patent Classification code[3]. *Discrete* technology areas are pharmaceuticals, biotechnology, and chemicals, where *complex* technologies include telecommunications, electronics, semiconductors, and information technology. As column 1 shows, there is a clear pattern of lower decentralization probability for complex technologies. The base category is pharmaceuticals, and the sample average probability of decentralization is 18.1%. Among the discrete technologies, there is not much difference in decentralization probability relative to pharmaceuticals. For example, the marginal effect of the biotechnology dummy is 0.017 (a standard error of 0.006), which indicates the probability of decentralization in biotechnology is only higher by 1.7 percentage points than the probability of decentralization in pharmaceuticals. However, striking differences emerge when examining the more complex technologies. The marginal effect of telecommunications is -0.105 (a standard error of 0.004), which means that the probability of decentralization in telecommunications is less than half the probability in pharmaceuticals. For information technologies and semiconductors, the results actually indicate that, on average, decentralization is completely muted. While the cross-industry results are definitely interesting and consistent with the predictions of the information processing and incentives theories, it is important to emphasize the low regression R^2 (0.038). As we would expect, a substantial fraction of the variation in our data is still left unexplained.

Second, our results suggest that patent quality and basicness is negatively related to decentralization. Here the general pattern of results is consistent with our *Hypothesis 1* which predicts that centralized R&D will be more scientific in orientation, broader in scope, and have more technical impact.We measure patent quality using the number of forward citations the patent receives over its life-cycle. Our *Basic* characteristics variables include the number of citations the patent makes to non-patent (scientific) literature, generality and originality[4]. The number of citations the patent makes to scientific article is

[3]Patent that are not classified to any of the main categories are classified under *Other.*

[4]We follow the widely accepted methodology developed by Trajtenberg, Henderson and Jaffe (1997) and define patent generality as inversely proportional to the concentration of the citations it receives

potentially an indication of the extent the patent relies on scientific knowledge. Generality is measured as the breadth of the technology areas across which a patent's citations are dispersed, and Originality is the equivalent measure for the citations contained in the patent. We find that, as predicted, centrally assigned patents tend to receive substantially more citations than decentralized ones. Based on the estimates of column 1, a one standard deviation increase in the number of citations received lowers the probability that a patent is assigned to an affiliate by 6.4 percentage points ($15.9 \times (-0.004)$), or by 35% percent of the average affiliation probability. Patent that are assigned to affiliates make fewer citations to non-patent literature than centrally-assigned patents. 106,617 patents make at least one non-patent citations. 85% of these patents are centrally assigned. A one standard deviation increase in the number non-patent citations lowers the decentralization probability by 3.1 percentage point ($3.9 \times (-0.008)$), or by 17 percent of the average affiliation probability. For generality, moving from the 10th percentile to the 90th percentile lowers decentralization probability by 2.5 percentage points ($1 \times (-0.025)$), or by 13.8% of the average affiliation probability. For originality, the effect is small. Moving from the 10th percentile to the 90th percentile lowers decentralization probability by about 4% of the average affiliation probability. Column 2 confirms these results continue to hold when we exclude those patents that receive no citations from the estimation sample.

Third, column 3 shows a positive effect of technical diversity on decentralization probability, also consistent with Hypothesis 2. Controlling for patents stock and sales, firms that patent in more diverse areas, as indicated by the value of their Unrelated Diversification, have on average a higher decentralization probability (a marginal effect of 0.024). Moving from the 10th to the 90th percentile of Unrelated Diversification, raises the probability of decentralization by about 41% of the mean ($\frac{0.024\times 3.1}{0.181}$). Interestingly, controlling for diversity, citations-received is no longer significantly associated with decentralization

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across technology areas. Patent i's generality, G_i, is computed as:

$$G_i = 1 - \sum_j \left(\frac{C_{ij}}{C_i}\right)^2 \tag{2}$$

Where, j denotes citing three-digit U.S. class (419 classes), C_{ij} is the number of citations received by patent i from patents in technology field j and C_i is the total number of citations received by patent i. Following Hall (2002) we correct G_i for the number of citations received, as $\widehat{G_i} = \left(\frac{C_i}{C_i - 1}\right) G_i$.

In addition to patent generality, we also include patent originality, which is the equivalent measure for the concentration across technology fields of the citations *made* by the patent.

(a marginal effect of -0.001 and a standard error of 0.001).

Column 4 reports OLS results of estimating a within-firm specification using a linear probability model. Comparing column 4 with column 1, we see that controlling for patent characteristics, firm fixed effects explain a very large fraction of the variation. Specifically, including firm fixed effects raises the R^2 from 0.04 in column 1 to 0.47 in column 4. This is consistent with the idea that patent decentralization reflects underlying organization structure, or at the very least, firms differ systematically in the extent to which they assign patents to affiliates. Columns 5 and 6 distinguish between pre and post-MA patents. Column 5 excludes patents by acquired affiliates that were granted before the acquisition year (thus, focusing only on internally developed patents), and column 6 excludes patents by acquired affiliates that were granted after the acquisition year (thus, focusing only on acquired patents). The same pattern of results holds for the two subsamples.

Insert Table 3 here

4.2 Implications of decentralization for innovation

We focus on three types of innovative activities: total R&D, patents per R&D, and publications of scientific articles.

4.2.1 R&D equation

As discussed in section 2.2, the theories we consider in this paper do not have clear implications for how R&D and patenting are related to decentralization. Cognizant of this limitation, we proceed to estimate the relationship between decentralization and R&D expenditures and the firm propensity to patent. The R&D equation is specified as:

$$\ln R\&D_{it} = \gamma_1 \ln Sales_{it-1} + \gamma_2 \ln(1 + GPat_{it-1}) + \gamma_3 ShareDec_{it-1} + \tau_t + \eta_j + \epsilon_{it} \quad (3)$$

The relationship between decentralization and R&D is captured by γ_3. According to incentives theories, delegation of authority encourages innovation efforts, hence we expect we expect $\widehat{\gamma}_3 > 0$. The information based theories, on the other hand, emphasize the importance of knowledge location and the costs that are associated with its transmission within the organization. While the benefits of decentralization lie in reducing the need for costly communication, the downside of decentralization is reduced coordination and lower knowledge spillovers across different parts of the firm. Insofar as the payoffs from R&D increase with knowledge spillovers, decentralization would be associated with lower R&D investment. This means $\widehat{\gamma}_3 < 0$. On the other hand, reduced coordination can also result in duplicative R&D, implying $\widehat{\gamma}_3 > 0$.

Table 4 reports the estimation results. The general pattern suggests a negative relationship between decentralization and R&D investment. As shows in column 1, the coefficient estimate on share decentralized is negative and is highly significant -0.157 (a standard error of 0.061). The R&D-decentralization relationship is particularly strong for firms with many patents (column 3). Results are robust for pre and post-acquisition patents (columns 4-5), however, not for within-firm estimation (column 6). Columns 7-9 report a very similar pattern for specifications where the dependent variable is $ln(R\&D/Sales)$.

Based on the estimation results of column 1, a one standard deviation increase in the share of decentralized patents lowers R&D investment by \$7.6 million ($-0.157 \times 0.44 \times 110$), or by 7% of the sample average.

Insert Table 4 here

4.2.2 Patent and publication equations

We next investigate the patent equation - namely, the output of the R&D equation. The patent flow equation (at the firm-year level) is specified as[5]:

$$\ln(1 + Pats)_{it} = \delta_1 \ln Sales_{it-1} + \delta_2 \ln GRD_{it-1} + \delta_3 ShareDec_{it-1} + \tau_t + \eta_j + \epsilon_{it} \tag{4}$$

The relationship between patent propensity and decentralization is captured by δ_3.

We estimate an equivalent specification for the flow of scientific publications. If decentralized firms are less likely to engage in basic R&D, we expect a negative $\widehat{\delta}_3 < 0$.

Columns 1-5 in Table 5 report the estimation results for patents. Column 1 shows a negative and significant relationship between decentralization and patent propensity. The coefficient on share decentralized is -0.0195 (a standard error of 0.058). This pattern is robust to pre and post acquisition patents, outliers, and weighting patents by citations.

[5] All results are robust to alternative specifications, such as Negative Binomial for patents count.

Based on the estimate from column 1, a one standard deviation increase in share decentralized is associated with 2.4 fewer patents per year, or 9% of the sample mean, given R&D ($-0.195 \times 0.44 \times 28$).

Columns 6-9 report the equivalent specifications for the yearly flow of academic publications. The general pattern of results suggests a strong negative relationship between decentralization and scientific publications. As shown in column, the coefficient on share decentralized is -0.171 (a standard error of 0.049). This e estimate drops substantially, however it remains highly significant, when controlling for patents stock (a coefficient of 0.118 and a standard error of 0.047).

Insert Table 5 here

4.3 Implications of decentralization for market value and growth

4.3.1 Market value

Given the novelty of our measure of decentralization, we begin by establishing that it is prima facie interesting. To this end, we estimate a simple version of the value function approach proposed by Griliches (1981)[6]. The market value of firm i at period t, V_{it}, takes the following form:

$$\begin{aligned} \ln Value_{it} &= \alpha_1 \ln Assets_{it-1} + \alpha_2 \ln GRD_{it-1} + \alpha_3 \ln(1 + GPat_{it-1}) \\ &\quad + \alpha_4 ShareDec_{it-1} + \tau_t + \eta_j + \epsilon_{it} \end{aligned} \tag{5}$$

$Value$ denotes firm market value, $Assets$, GRD and $GPat$ denote physical, R&D, and citations-weighted patent stocks, respectively. $ShareDec$ is our main variable of interest, and is constructed as the share of the firm patents stock that is assigned to affiliates. τ_t and η_j and are complete sets of year and three-digit industry dummies, and ϵ_{it} is an *iid* error term. The reported standard errors are always robust to arbitrary heteroskedasticity and allow for serial correlation within firms. α_4 captures the decentralization-value relationship.

Table 5 reports the estimation results for the market value equation. Column 1 includes separately the stocks of centralized and decentralized patents. The coefficient on

[6] See also Jaffe (1986), Hall et al (2005) or Lanjouw and Schankerman (2004).

centralized patents stock is not significantly different than zero (a coefficient of 0.018 and a standard error of 0.014), where the coefficient on decentralized patents stock is large and is highly significant (a coefficient of 0.091 and a standard error of 0.015). Column 2 controls for ownership structure by adding the total number of affiliates controlled by the firm, and for scale using firm sales. The effect of decentralized patents remains robust, however drops in magnitude (a coefficient of 0.071 and a standard error of 0.014). The coefficient on number of affiliates is positive and significant (0.043 and a standard error of 0.017).

In column 3, instead of separately including the stocks of centralized and decentralized patents, we include the overall stock of patents, and the share of patents that are decentralized. The coefficient on the share of decentralized patents is positive and significant (a coefficient of 0.217 and a standard error of 0.052). The coefficient on overall patents stock is positive and significant as well (0.057 and a standard error of 0.016). Column 4 adds number of affiliates and sales. The coefficient on the share of decentralized patents drops, but remains large and highly significant (0.159 and a standard error of 0.048).[7]

Column 6 controls for the firm stock of scientific publications. Our findings indicate that publishing firms have, on average, a lower market value than comparable non-publishing firms. The coefficient on publications stock is -0.054 (a standard error of 0.018). The effect of share decentralized remains robust (a coefficient 0.157 and a standard error of 0.044).

Columns 6-9 examine the robustness of the results. Column 3 includes a dummy for decentralization. This dummy receives the value of one for firms for which at least 50% of their patents are assigned to affiliates, and zero for all other firms. Consistent with our previous findings, the coefficient on this dummy is positive and highly significant (0.157 and a standard error of 0.044). Columns 7-9 check the robustness of the results

[7] In unreported specifications, we include a set of three separate indicator variables that capture the non-linear effect of decentralization. For each firm we assign a value of 1 to only one of these dummy variables based on which pattern best describes the firm's patents: all patents are centrally assigned (share decentralized is zero); share decentralized is between zero and 0.2; share decentralized is between 0.2 and 0.8; share decentralized is above 0.8. Using the zero-share decentralization subset as our base category, we find that the value-decentralization relationship is driven mostly by firms where at least 20% of their patents are decentralized. The coefficient on dummy for zero to 0.2 decentralization share is not statistically significant (a coefficient of 0.110 and a standard error 0.068). The coefficient on dummy for decentralization share higher than 0.8 is 0.173 (a standard error of 0.063), while the coefficient estimate for 0.2-0.8 decentralization range is 0.256 (a standard error of 0.068).

for different subsamples. Columns 7 excludes very large patenting firms[8], and columns 8 and 9 distinguish between pre and post-acquisition patents. The results are robust for the different samples.

Based on the estimated coefficient reported in column 3, a one standard deviation increase in share decentralized is associated with an increase in firm value by $137 million ($0.217 \times 0.44 \times 1431$), or 9.6% of the average firm value. Note well that no causal inference is asserted here. We are not claiming here that a centralized firm would do well to decentralize, nor of course the converse. Instead, we are content to observe for now that our measure of decentralization is systematically related to market value of the firm, controlling for size, tangible assets,R&D stock, and industry, and that this relationship survives a variety of robustness checks described above. Simply put, there is a prima facie case for further exploring the determinants and correlates of decentralization.

In addition to estimating the linear market value specification, we experiment with estimating linear and non-linear Tobin's Q specifications. For brevity, we do not discuss these estimations in detail. The same pattern of results hold for linear and non-linear Tobin's Q specifications[9]. For example, in the linear specification the coefficient on the share of decentralized patents is 0.224 (a standard error of 0.049). A nonlinear estimation yields a higher estimate (a coefficient of 0.308 and a standard error of 0.050).

Insert Table 6 here

4.3.2 Sales growth

We proceed to explore the impact of decentralization of R&D on firm sales growth. We estimate the following sales growth equation:

$$\begin{aligned}\Delta \ln Sales_{it} = {} & \beta_1 \ln Sales_{it-1} + \beta_2 \ln Assets_{t-1} + \beta_3 \ln GRD_{it-1} + \beta_4 \ln(1 + GPat_{it-1}) \\ & + \beta_5 ShareDec_{it-1} + \tau_t + \eta_j + \epsilon_{it}\end{aligned} \tag{6}$$

[8] These companies are IBM, General Electric, Motorola, Hewlett-Packard, and Eastman Kodak.

[9] In columns 1-7 we approximate $ln(1 + \alpha_2(GRD/Assets)_{it-1} + \alpha_3(GPat/Assets_{it-1}))$ to $(\alpha_2(GRD/Assets_{it-1}) + \alpha_3(GPat/Assets_{it-1}))$. In columns 8-10 we do not make such approximation and estimate the non-linear term using Non-Linear Least Squares.

Where $\Delta \ln Sales_{it}$ is $\ln Sales_{it} - \ln Sales_{it-1}$. β_5 captures the relationship between decentralization and sales.

Table 7 reports the estimation results. Column 1 examines the decentralization-growth relationship. Consistent with our findings for market value, the coefficient on share decentralized is positive and is highly significant (0.037 and a standard error of 0.010). Column 3 includes publications stock. The coefficient on publications stock is effectively zero (0.001 and a standard error of 0.003). Column 3 excludes very large patentors with no change in the results. Columns 4 and 5 distinguish between post and pre-acquisition patents. The same pattern of results holds for both subsamples, however, the effect of decentralization appears to be higher in the latter subsample (a coefficient of 0.040 and a standard error of 0.010, versus a coefficient of 0.021 and a standard error of 0.011, for pre and post-acquisition patents, respectively). As shown in columns 6-8, the results are not sensitive to including firms with many or few patents, or when considering a two-year sales growth. These findings are consistent with our Hypothesis 1, insofar as it predicts decentralized R&D will be less scientific, given that it would thus be more likely to be commercializable.

Insert Table 7 here

4.3.3 Diversity

Our Hypothesis 1 predicts a positive relationship between decentralization and broader scope of research jointly condition market value of the firm. According to information processing, the benefits from decentralization are more prominent as patenting diversity increases. This is because the benefits from specialization increases with complexity . and because the communication of information becomes more costly in more diverse organizations. Moreover, the cost of decentralization is lower when divisions focus on very different tasks as the scope for spillovers and rent cannibalization is reduced. On the other hand, under the incentives view, the decentralization-value relationship should not systematically vary with diversity, since incentives can be very important also in highly specialized organizations. We Follow Palepu (1985) and construct firm technological diversity as the Entropy measures, which include *Total Diversification (TD)*, *Related Diversification (RD)*, and *Unrelated Diversification (UD)*. These measures are constructed as follows. Suppose a firm operates in N segments which belong to M main technology areas. We use three-digit and two-digit U.S. class to define segments and technology areas, respectively. We denote by P_i^j the share of the i^{th} segment patents of total firm patents in technology area j. Related diversification measures the extent the firm operates in several business segments *within* an industry, and is defined as:

$$RD_j = \sum_{i \in j} P_i^j \ln\left(\frac{1}{P_i^j}\right)$$

If a firm operates in several technology areas, its aggregated related diversification is the weighted sum of RD_j, where the weight, P_j, is the share of technology area j patents of the firm's total patents.

$$RD = \sum_{j \in M} RD_j P_j \qquad (7)$$

Unrelated diversification measures the firm patents spread across different (two-digit) technology areas, and is defined as:

$$UD = \sum_{j \in M} P_j \ln\left(\frac{1}{P_j}\right) \qquad (8)$$

Total Diversification (TD) is a weighted average of the firm's diversification within and between sectors and is computed as the sum of *RD* and *UD*.

We estimate the following specification:

$$\ln Value_{it} = \alpha_1 ShareDec_{it-1} + \alpha_2 ShareDec_{it-1} \times Diversity_i + Z'_{it-1}\alpha_5 + \tau_t + \eta_j + \epsilon_{it} \quad (9)$$

$Diversity_i$ is one of the above diversification measures, and Z is a vectors of additional firm-level controls. Our main interest is the coefficients α_2 and α_3. Consistent with information processing, we expect $\widehat{\alpha}_2 > 0$. That is, the marginal value of decentralization intensifies as the corporation becomes more diverse. On the other hand, consistent with the incentives theory, there is no clear reason to suspect the marginal value of decentralization to rise with diversity ($\widehat{\alpha}_2 = 0$).

The estimation results are reported in table 8. Columns 1 and two estimates the baseline market value equation separately for specialized and diversified firms. We classify firms as specialized if their value of *Unrelated Diversification* falls in the lowest sample quartile, and as diversified if their respective diversification value falls at the highest diversification quartile. The coefficient on share decentralized is large and significant for the diversified sub-sample (0.359 and a standard error of 0.086), and is small and insignificant for the specialized firms sub-sample (0.047 and a standard error of 0.112). Column 3 adds to the baseline specification the interaction between Total Diversification and share decentralized. Consistent with the information processing view, the coefficient on this interaction ($\widehat{\alpha}_2$) is positive and significant (0.011 and a standard error of 0.004). The coefficient on share decentralized remains positive and significant (0.117 with a standard error of 0.057). Next we decompose diversification to within and between technology areas. Column 4 includes the interaction between share decentralized and Unrelated Diversification. The relationship is very strong. The interaction coefficient is 0.140 (a standard error of 0.096), where the level effect of share decentralized is no longer significant (a coefficient of -0.096 and a standard error of 0.108). Columns 5 includes the interaction between Related Diversification and share decentralized, which yields much smaller estimates of how the effect of decentralization of market value varies with firm diversity (a coefficient of 0.011 and a standard error of 0.005).[10]

Based on the estimates of column 4, evaluated at the sample average, a one standard deviation increase in share decentralized is associated with a $95 million increase in market value ($0.44 \times (-0.096 + 1.76 \times 0.140) \times 1431$). This figure is substantially lower than the $137 million figure than is based on the estimates from table 5 where we did not control for diversification. A one standard deviation increase in diversity almost doubles the effect of decentralization to $182 million ($0.44 \times (-0.096 + (1.76 + 1) \times 0.140) \times 1431$).

Columns 6 includes an alternative measure of diversity - Herfindahl-Hirschman Index (HHI) of patent concentration across three-digit U.S. technology class. The same pattern of results continue to hold.

[10] An important concern is that the interaction between decentralization and diversity is driven by patenting scale. By construction, firms with fewer patents are likely to be less diverse than firms with many patents. If decentralization is more important for market value for firms with few patents than firms with many, $\widehat{\alpha}_2$ would be upward biased. To mitigate this concern we check the robustness of the estimates reported in column 4 to adding an interaction between $ShareDec$ and $\ln(1 + GPat_{it-1})$. The coefficient on the interaction term between $ShareDec$ and *Unrelated Diversification* falls to 0.093 (from 0.140), but it remains significant (a standard error of 0.044). To further check the variation in our data does not stem solely from comparing firms with few patents to firms with many patents, we restrict the sample to include firms with above median patents stock. The coefficient on the interaction term between $ShareDec$ and *Unrelated Diversification* is 0.126 (a standard error of 0.041).

Lastly, column 7 investigates the extent to which the marginal value of decentralization varies with geographical diversity. Similar to the above theoretical arguments, if communication costs increase when the corporation's R&D labs are more geographically dispersed, we would expect the marginal value of decentralization to rise with geographical diversity. We measure geographical diversity in the following way. For each corporation, we generate a list of all inventors and their location as indicated on the patent document. We then construct the Herfindahl-Hirschman Index (HHI) of patent concentration across American cities (excluding foreign inventors). The results are once again consistent with the information processing story: the coefficient on the interaction term between geographical diversity and decentralization is negative and is highly significant (-0.598 and a standard error of 0.191).

Insert Table 8 here

4.4 Reassignment

We determine whether a patent is assigned to an affiliates or headquarters by examining the assignee name that appears on the patent document when it was granted. However, assignees can change over the patent life-cycle. Reasons for reassigning a patent include a merger or an acquisition, or a managerial decision within-firms of how to allocate IP assets across the organization units. Using data on reassignments, as coded by the USPTO, we test the robustness of our key results. 41,244 patents in our sample are reassigned. Close to 90% of these reassignments are assigning a patent from headquarters to an affiliate (36,180 patents). There is no big difference in the share of reassigned patents between M&A and internal patents. For M&A patents, 8% are reassigned (8,410 patents), where for internal patents, 7% are reassigned (32,834 patents). For M&A-related reassignments, 23% are reassignments from affiliates to headquarters, where for internal patents, about 91% of reassignments are from headquarters to affiliates.[11]

[11] In terms of citations, reassigned patents receive substantially fewer citations than patents that are never reassigned. The average reassigned patent receives 4.3 citations, where the average non-reassignment patent receives 9.9 citations. This pattern robust for period effects. For example, for patents granted post 2000, reassigned patents receive, on average 4 citations, relative to 9.5 citations for patents with no reassignment that are granted in the same period. The pattern holds for patents granted before 2000, and for alternative time cohorts.

We repeat our estimations by accounting for changes in reassignments. For brevity we do not report the full set of results. Our findings are robust to reassignment. For example, for market value, the coefficient on share decentralized is 0.181 (a standard error of 0.048), as compared to a coefficient estimate of 0.159 in the equivalent specification that does not accounts for reassignments (Table 4, column 4).

5 Conclusions

This paper develops a new way, using patent data of measuring the organization of R&D in a firm, in order to explore the impact of firm organization on performance variety of outcomes, including the extent and nature of research activity, as well as sales growth and market value.

We use data 1,290 American publicly-listed corporations, with 2,615 Patent-receiving affiliates, as well as characteristics of 594,903 patents that belong to these corporations. Our key measure is whether a patent is assigned to the parent corporation or to an affiliate. The assignment of intellectual property to a wholly owned affiliate cannot have legal significance. However, it likely reflects a de facto delegation of authority to the affiliate in how the R&D is managed, a suggestion which is supported by our interviews with managers. . Indeed, consistent with the notion that patent assignments to affiliates reflects an underlying decentralization of R&D to the affiliate, we find that decentralized patents are less likely to cite scientific papers, less general in scope, and receive fewer citations. Firms that extensively decentralize patents are also less likely to produce scientific publications, and more likely to rely upon mergers and acquisitions to acquire patents.

We next turn to the relationship between decentralization and outcomes. We find that firms that decentralize R&D invest less in R&D, and given their R&D investment, produce fewer patents. The may reflect the efficacy of decentralized R&D, or the more incremental nature of decentralized R&D, or merely difference in incentives to patent. We also find that decentralization of R&D is associated with greater sales growth, and higher market value, suggesting that whereas centralized research may be technically and scientifically superior, the private economic benefits are less clear cut.

Given that the nature of research and the choice of organizational forms are jointly determined, and related to unobserved factors such as technological opportunities, one cannot infer causal impacts of organizational form on performance. Neither can we conclusively discriminate between different theoretical perspectives. Our results support the view that decentralization economizes on communication between affiliates and firms, at the possible cost of reduced coordination. Over and above these findings, this project contributes by revealing a new way of using patent data to proxy for differences in organizational structure.

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A Appendix

This section details the construction of the data platform used in this project. The central datasets consist of a patent-level panel and a firm-level panel, which are linked via the unique patent id numbers. Each of these panels is built up iteratively, by incorporating data from the following sources: (i) patent level information from the United States Patent and Trademark Office (USPTO), (ii) ownership structure data from Icarus and Amadeus by Bureau Van Dyke (BVD), (iii) Merger and acquisition data from Thomson Reuters SDC Platinum and Zephyr by Bureau Van Dyke, (iv) accounting information from U.S. Compustat, and (v) extensive manual searches of on-line resources, such as corporate and governments websites, and search engines.

A.1 Ownership Structure

Assignee information is available from the USPTO, but many of the patent assignments are made to affiliate firms. Furthermore, firms vary in their choice to utilize affiliates for their assignments, resulting in noisy (at best) or biased (likely) patent and citation counts at the firm level. As Hall, et al. (2001) put it:

"There is a further reason for this to be a lower bound: the assignee code is not "consolidated", that is, the same firm may appear in different patent documents under various, slightly different names, one assignee may be a subsidiary of the other, etc. Thus, if for example we were to compute the percentage of self-citations using the Compustat CUSIPs (after the match) rather than the assignee codes, we would surely find higher figures."

Thus, our goal is to trace the chain of ownership for every relevant patent precisely back to the Compustat CUSIP identification number. Below, we detail the steps taken.

A.1.1 Control chain generator.

The linchpin of this project is the identification of an ultimate owner ("UO") for a large portion of the companies reported as patent assignees by the USPTO. Here we follow the methodology employed by Belenzon and Berkowitz (2010). We obtain ownership structure data from the Icarus and Amadeus databases by Bureau Van Dyke (BVD). The Amadeus ownership database includes detailed information of the percentage of ownership between shareholders and their subsidiaries. We develop an ownership algorithm that constructs the internal structure parent and affiliate groupings based on their inter-company ownership links.

The algorithm follows three steps: (i) completes missing ownership links, (ii) generates lists of all subsidiaries and parents for each company, and (iii) constructs the ownership chains bottom-up. To illustrate our methodology, it would be useful to consider the following example. Suppose Figure A.1 correctly describes the ownership structure of a conglomerate. The ultimate owner firm at the apex of the group controls 7 public and private firms. Amadeus provides detailed data on direct ownership links. Thus, our raw data include the links $A \to D$, $B \to F$, $C \to G$, and $D \to E$. Note that the percentage of ownership for the link $C \to G$ has to be larger than 20 (because firm G is public), where for the percentage of ownership for all other links has to be larger than 50 (because the other subsidiaries are private). Because there is no information about indirect ownership links, the link $A \rightarrow E$ is missing from the raw data. The first step of the algorithm is to complete missing links. As we observe the ownership relations $A \rightarrow D$ and $D \rightarrow E$, our algorithm infers the ownership relation $A \rightarrow E$. Note that at this stage of the algorithm we still do not know whether the ownership relation is direct or indirect (and if it is indirect, how many layers separate firm E from firm A). The second step of the algorithm is to construct two lists for each firm: shareholders and subsidiaries. This step saves valuable running time, which is especially important when dealing with large scale ownership data. The following table is generated:

Firm	Shareholder	Subsidiary
A	-	D, E
B	-	F
C	-	G
D	A	E
E	A, D	-
F	B	-
G	C	-

Note that from step 1, we already know that firm A is a shareholder of firm E. The third and final step of the algorithm is to construct the structure of the group based on the above ownership relations. Because of the missing links problem, our algorithm does not assume that an ownership relation is direct; the only input the algorithm receives is the existence of the ownership relation. We start with a firm that has no subsidiaries from the list generated in step 2. We illustrate the procedure for firm E, which is the most interesting in this example. Firm E is placed at the bottom of the ownership chain. Next, we move to the shareholder list of firm E. It includes firms A and D. Starting arbitrary with A, place A above E. Proceeding to firm D, there are three possibilities for its location: (i) D is above E and above A; (ii) D is above E, but below A; (iii) D is above E, but not below neither above A (different ownership chain). For (i) to be the right structure, D has to appear in the shareholder list of firm A. From step 2, we rule this out. For (ii) to be the right structure, D has to appear on the subsidiary list of firm A. From step 2, we rule this out. For (ii) to be the right structure, D has to appear on the subsidiary list of firm A. From step 2, this holds. Finally, for (iii) to be the right structure, A cannot appear on either the shareholder or subsidiary lists of firm D. From step 2, this is ruled out. At the end of this procedure, we have determined for each ownership chain the highest shareholder firm - we call this firm the leading shareholder.

A.1.2 Dealing with M&A

A central issue in our analysis is the post-merger management of acquired firms. The decentralization variation in our data comes mostly from two sources: the degree of post-acquisition integration of affiliates (with a lower bound being those kept independent), and the speed at which patents are generated centrally in relation to existing affiliates. For each acquired firm we determine whether it remained independent post-acquisition, or whether it was dissolved. We take several steps in determining whether a firm is independent. First, we check whether the firm appears in Amadeus or Icarus as an independent company. Second, we manually check each company listed in the first step whether it continues to operate independently from the parent company. We check their corporate websites to confirm that their legal disclaimers and investor relations information references a parent company.

Dissolved acquisitions are much more problematic. Because we match patents to firms based on the 2008 ownership structure, we lose historical acquisitions that were fully integrated in the parent company and ceased to exist as separate legal entities. Though we do capture post-acquisition patents as those are likely to be assigned to headquarters, we may nonetheless over measure decentralization (because all historical patents that we do not match are centralized). To mitigate this problem we take two steps. We match all firms in SDC Platinum where the acquiring firm appears in our sample. We then add to our data all patents that belong to acquired firms that no longer appear in the 2008 data. SDC platinum is likely to miss smaller acquisitions, so we also did an extensive search of public sources (such as Lexis-Nexis,EDGAR and general web searches) to generate a list of all acquisitions for the top 500 patenting corporations in our sample. As this is an iterative process, the resolution of M&A issues was not completed until the final stages of all our patent and firm matching (i.e. this last step would have been taken after the completion of A.2.1 below). For acquisitions that do not appear in SDC we classify its patents as follows: if the firm is active in 2008 (thus, it is matched to one of the firms in our firm universe) then we classify it as an affiliate of the acquiring corporation. However, in case there is no match between this firm and our firm universe, we classify all of its patents to the acquiring firm headquarters.

Overall, we matched 50,931 patents to SDC and Zephyr. An underlying assumption of this matching is that an affiliate exists in 2008. If the affiliate was historically dissolved it will not appear in our firm universe, hence, its patents will not be included in our sample. In order to overcome this problem, we take two steps. First, for the largest 500 patenting corporations in our sample we manually collect data, from public sources, on their historical acquisitions. This list allows us to identify those firms that were acquired and fully dissolved. Second, we generate a list of the top 1,000 American assignees (as indicated by the address of the assignee) that were not matched to our data. The remaining unmatched firms have less than 40 patents over their lifetime, so it is reasonable to assume that they are not patent-intensive firms. For each unmatched firm remaining in our sample, we manually investigate whether it was acquired by any of our sample parent corporations, or by any firms that themselves were acquired by our parent corporations. These two steps lead us to identify 53,761 patents, which we proceed to classify as centrally assigned. In total, we identify 104,692 as being acquired through a merger or an acquisition. Of these patents, 55,702 (53%) are assigned to affiliates, and the remaining patents are assigned to headquarters.

For each acquired firm we determine whether it remained operational post-acquisition. We take several steps in determining whether a firm is independent. First, we check whether the firm appears in Amadeus or Icarus as an independent company. Second, we manually check each company listed in the first step whether it continues to operate independently from the parent company. We check their corporate websites to confirm that their legal disclaimers and investor relations information references a parent company.

Dissolved acquisitions are much more problematic. Because we match patents to firms based on the 2008 ownership structure, we lose historical acquisitions that were fully integrated in the parent company and ceased to exist as separate legal entities. Though we do capture post-acquisition patents as those are likely to be assigned to headquarters, we may nonetheless over measure decentralization (because all historical patents that we do not match are centralized). To mitigate this problem we performed an exhaustive manual search to identify a significant majority of these absorbed firms and match them to their patents. Appendix A.1.3 for a description of this process.

A.2 Matching patent data

We standardize a name cleaning algorithm that is run both on the UO dataset and the 2007 NBER Patent and Citations Dataset in order to match observations by company name. We utilize the assignee codes contained in NBPATS only as quality checks, or for guidance in manual searches, however we concentrate on matches using the affiliate company names and our ultimate owner company names from UO. The algorithm utilizes both automated rules and manual inputs to reduce most firm names to a one or two word string variable. Extensive testing was performed to yield the highest rates of matching, while minimizing multiplicity errors (which occur when two distinct names are rendered equal by deleting distinguishing words). Like previous work in name matching, we capitalize all letters, and remove extraneous characters and strings such as "&," "THE," "ASSOCIATES," etc. We compile a list of 175 most common such "junk" words (i.e. non-essential for uniquely identifying companies). Our list is more targeted to American firms (our focus) than those lists developed by the NBER Patent Data Project. Furthermore, one refinement over previous such name matching projects is our use of a process whereby junk words are truncated in a right-to-left fashion. This increases the match yield significantly, as we are able to remove, for example, the word "INTERNATIONAL" from "PIONEER HI-BRED INTERNATIONAL, INC," (because it occurs on the right side) while allowing it to remain in "INTERNATIONAL BUSINESS MACHINES CORPORATION." To illustrate, the truncation would proceed as follows:

1. Pioneer Hi-Bred International, Inc.
2. PIONEER HI-BRED INTERNATIONAL, INC. (capitalize)
3. PIONEER HI BRED INTERNATIONAL INC (remove punctuation)
4. PIONEER HI BRED INTERNATIONAL (remove last word if "junk")
5. PIONEER HI BRED (remove last word if "junk." Stop)

Here, the algorithm stops when it reaches a "non-junk" word. For "INTERNATIONAL BUSINESS MACHINES CORPORATION," it would have stopped after truncating the word "CORPORATION."

We can further see the power of this "right-to-left"approach by looking at the way that the sub string "HI" above is treated under a different set of conditions. Consider the name "VERIZON INC/HI" (it is common in Compustat to include state identifiers):

1. Verizon Inc./HI
2. VERIZON INC./HI (capitalize)
3. VERIZON INC HI (remove punctuation)
4. VERIZON INC (remove last word if "junk.")

5. VERIZON (remove last word if "junk." Stop)

Here, the sub string "HI" is properly removed, whereas removing it from Pioneer Hi-Bred would have resulted in a corruption of the identifier.

One of the tradeoffs in matching is always between high yield and multiplicity errors. For example, one can see how too aggressive an algorithm can render "American Express," "American Airlines," and "American Standard" into "AMERICAN." Our choice was to err on the side of higher multiplicity, but to rely on manual checks to correct any mis-coded companies. By always keeping track of the original, uncleaned names, we added extra steps to check any duplicates (i.e. cases where the same cleaned name corresponded to more than one original name). At this stage, extensive manual effort was expended to resolve ambiguities by performing actual checks of patent images and web searches. Ultimately, we match over 846,000 patents to our UO file.

A.2.1 Matching to Compustat

Having matched patents to firms to ultimate owners, we proceed to match as many ultimate owners as possible to a CUSIP (in order to tap into Compustat accounting information). Because only publicly traded companies are listed by Compustat, this effectively serves as a filter to eliminate government and institutional entities that may have mistakenly made it into our sample by this point. We utilize the standardized matching algorithm used in A.2.1, with some modifications to account for idiosyncratic Compustat "junk words."

A.3 Reassignments

Our measures of assignment structure depend on the assignee name that appears on the patent document when it was granted, but patent assignment can change over time. To test the robustness of our results to changes in assignment, we develop comprehensive data on patent reassignment by using data collected from the USPTO website. Reassignment data is collected using a specialized automated "spider" web-crawler program. This data is then searched for content, processed and merged to our final patent sample. We are interested in two reassignment types: (i) assigning a patent that was originally assigned to headquarters to an affiliates, and (ii) reassigning to headquarters a patent that was originally assigned to an affiliate. To determine reassignment type we match old and new assignees to our firm name sample. This matching is very challenging because many patents undergo multiple reassignments over their lifetime for reasons that are not germane to our study. For example, patents are very often reassigned to correct errors in the initial document, or for purposes of collateralization for lenders. This last case usually entails multiple transactions, such as when the collateral reverts to borrower, or when loans are assigned within financial institutions. Thus, we need to track the patent's path (including such diversions) over time. Ultimately, 41,244 patents in our sample are reassigned. Close to 90% of these reassignments are assigning a patent from headquarters to an affiliate (36,180 patents). Finding that reassignments from affiliates to headquarters are rare supports our view of assignments as being associated with a long-term effective

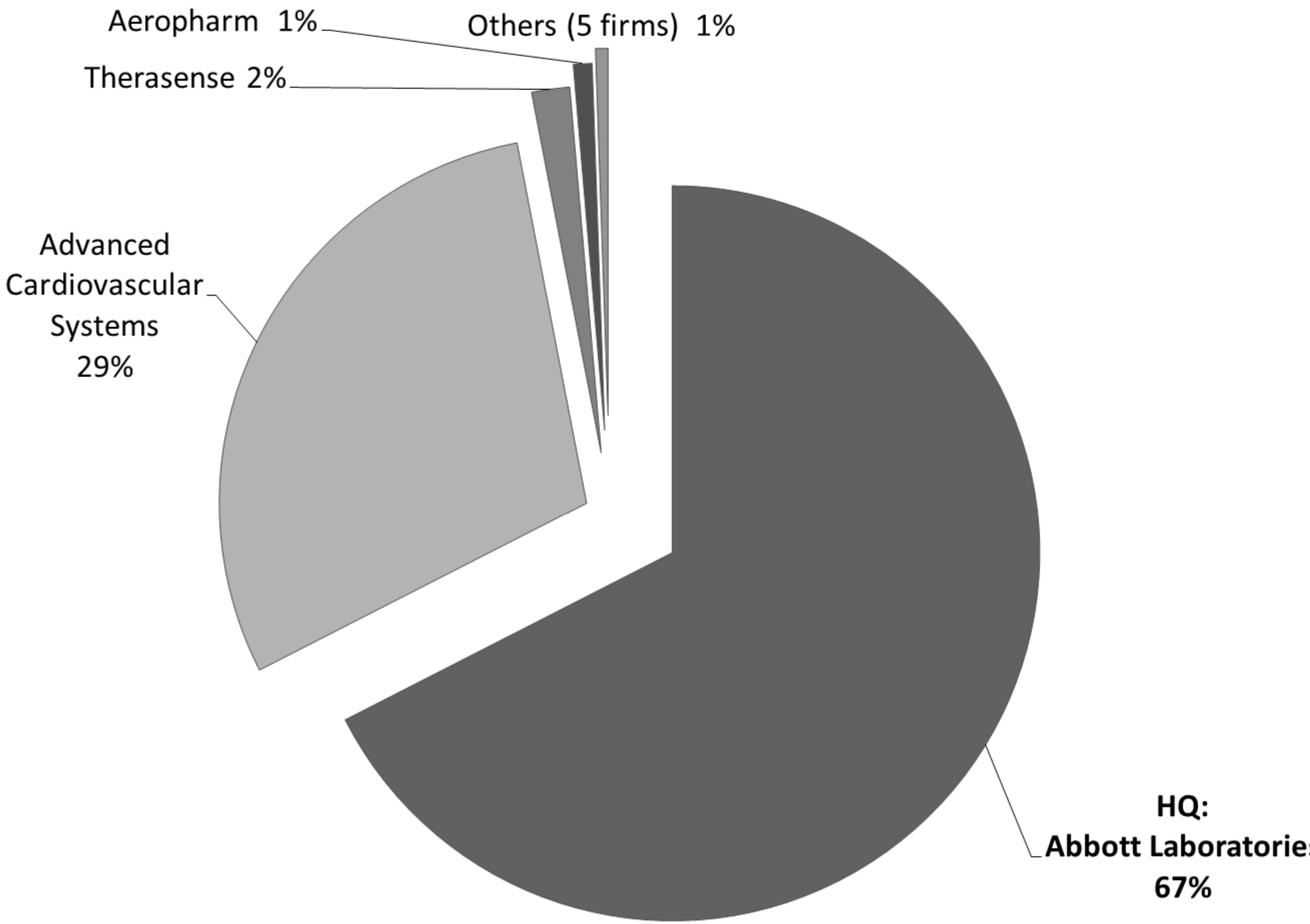

figure 1: Abbott Laboratories (example of a highly centralized firm)

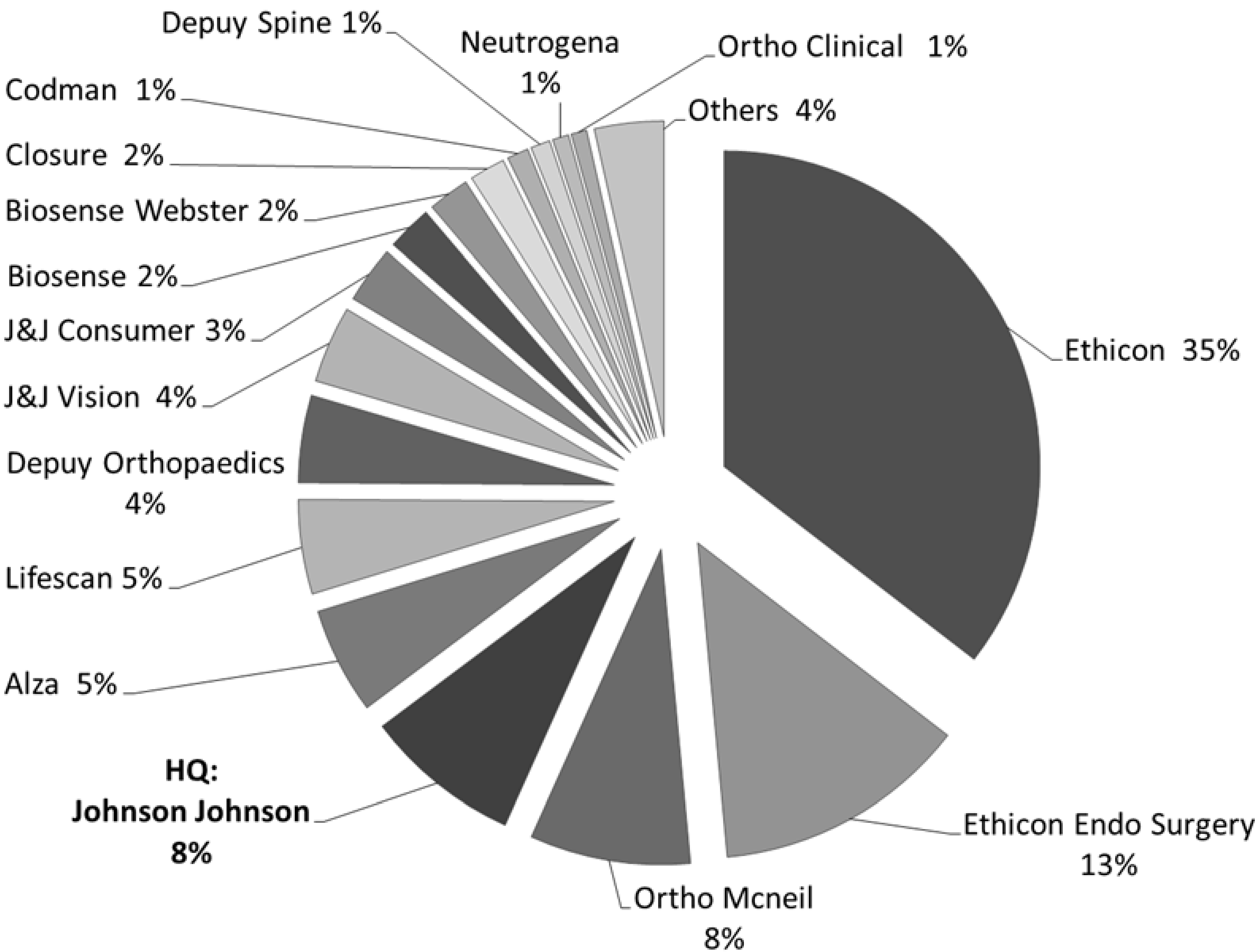

figure 2: Johnson & Johnson (example of a highly decentralized firm)

Table 1. Summary Statistics for Main Variables

Variable	*# Obs.*	Mean	Std. Dev.	Distribution 10th	50th	90th
Panel A: Firms (Firm-Year)						
Share Decentralized $_{t-1}$	15,821	0.36	0.44	0	0.03	1
Market Value ($mm)	15,821	1,431	7,113	4	128	2,949
Tobin's Q	15,727	1.13	2.08	0.13	0.58	2.25
Sales Growth	15,748	0.104	0.363	-0.118	0.084	0.357
Sales $_{t-1}$ ($mm)	14,330	3,633	12,034	34	598	8,256
Assets $_{t-1}$ ($mm)	14,257	2,085	7,281	11	201	4,619
R&D Expenditures ($mm)	15,821	110	470	0	5.4	185
R&D Stock $_{t-1}$ ($mm)	14,335	488	1,953	0	27	866
Patents Stock $_{t-1}$	15,821	132	575	0.1	10	209
Publications Stock $_{t-1}$	15,821	132	575	0.1	10	209
Patents flow	15,821	27	104	0	2	54
Publications flow	15,821	8.5	52	0	0	5
Panel B: Patents						
Dummy for Decentralized	594,903	0.18	0.39	0	0	1
Generality	403,800	0.57	0.32	0	0.66	1
Originality	433,449	0.27	0.28	0	0.22	0.67
Citations per Patent	594,903	8.9	15.9	0	4	22
Citations to Non-Patent Lit.	594,903	0.8	3.9	0	0	2
Citations to Non-Patent Lit. (>0)	106,617	4.3	8.3	1	2	9

Notes : This table provides summary statistics for key variables used in the econometric analysis. *Market Value* includes common stock, preferred stock and debt, net of current assets. *Tobin's Q* is the ratio between *Market Value* and *Assets* . *R&D Stock* is computed using the perpetual inventory method with a depreciation rate of 15%. *Patents Stock* is citations-weighted and is computed using the perpetual inventory method with a depreciation rate of 15%. *Share Decentralized* divides a firm's total number of affiliate-assigned patents by its total number of patents. In constructing *publications stock* we match our sample firms to the complete ISI database for the period 1970-2007. *Publications stock* is computed using the perpetual inventory method. *Generality* is the HHI measure of concentration of the citations a patent receives across three-digit U.S. class. *Originality* is the HHI measure of concentration of the citations a patent makes across three-digit U.S. class. *Citations to Non-Patent Lit.* is the number of citations a patent makes to non-patent literature.

Table 2. Correlations

	Share Decentralized	*Share M&A*	*Tobin's Q*	*Sales*	*Patents Stock*	*R&D Stock*	*Patents Flow*	*R&D Stock*
Share Decentralized	1.00							
Share M&A	0.41	1.00						
Tobin's Q	0.10	0.07	1.00					
Sales	0.05	0.14	-0.05	1.00				
Patents Stock	-0.14	0.09	-0.13	0.36	1.00			
R&D Stock	-0.14	0.07	-0.13	0.39	0.64	1.00		
Patents Flow	-0.11	0.08	-0.10	0.43	0.86	0.66	1.00	
R&D Flow	-0.04	0.12	-0.02	0.76	0.61	0.95	0.67	1.00

Notes: This table reports the correlation matrix between our key variables. *Share Decentralized* divides a firm's total number of affiliate-assigned patents by its total number of patents. *Share M&A* is the share of patents that are acquired through a merger or an acquisition. *Tobin's Q* is market value over assests.

Table 3. Patent Decentralization

Dependent variable: Dummy for Decentralization						
	(1)	(2)	(3)	(3)	(4)	(5)
		At least one cite		Within-firms	Post-M&A Patents	Pre-M&A Patents
ln(1+*Citations Received*)	-0.004**	-0.005**	-0.001	0.003**	-0.005**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(1+*Citations to Non-Patent Lit.*)	-0.008**	-0.009**	-0.007**	-0.001	-0.006**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Patent Generality	-0.025**	-0.026**	-0.022**	-0.012**	-0.017**	-0.022**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Patent Originality	-0.010**	-0.010**	-0.013**	0.001	-0.005**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm Diversity			0.024**			
			(0.002)			
Firm Patents Stock			-0.027**			
			(0.001)			
Firm Sales			-0.006**			
			(0.001)			
Technology areas dummies:						
Biotechnology	0.017**	0.012	0.002	0.033**	0.013**	-0.003
	(0.006)	(0.007)	(0.006)	(0.006)	(0.004)	(0.006)
Chemicals	-0.019**	-0.018**	-0.014**	-0.021**	-0.011**	-0.006
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Telecommunications	-0.105**	-0.096**	-0.080**	0.021**	-0.105**	-0.072**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)
Electronics	-0.109**	-0.102**	-0.095**	-0.019**	-0.103**	-0.079**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Semiconductors	-0.269**	-0.289**	-0.240**	-0.032**	-0.245**	-0.198**
	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
Information Technology	-0.190**	-0.185**	-0.157**	-0.006	-0.169**	-0.141**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Engineering	-0.031**	-0.023**	-0.041**	-0.024**	-0.018**	-0.017**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
R^2	0.0379	0.037	0.054	0.465	0.060	0.050
Observations	594,903	467,246	594,903	594,903	482,430	559,296

Notes: This table reports the estimation results of a Probit model that examines the determinants of decentralization. The base technology area is Pharmaceuticals. We assign specific codes, and include respective dummy variables for patents that receive (make) less than two citations. For these patents Generality (Originality) is not defined. All columns include an unreported Other technology category. Firm Diversity (column 3) is computed as the Total Diversification Entropy measure using patent IPC codes. Column 5 reports OLS results of a Linear Probability Model. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation. **, * denote significance levels of 1 and 5 percent, respectively.

Table 4. Research and Development

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	ln(*R&D*)						ln(*R&D*/*Sales*)		
		Patents ≤ median	Patents > median	Post-M&A Patents	Pre-M&A Patents	Within-Firms		Post-M&A Patents	Pre-M&A Patents
Share Decentralized $_{t-1}$	-0.157**	-0.098	-0.180**	-0.142*	-0.174**	0.009	-0.181**	-0.160**	-0.205**
	(0.061)	(0.102)	(0.066)	(0.070)	(0.066)	(0.055)	(0.060)	(0.068)	(0.064)
ln(1 + *No. Affiliates*)	0.015	0.088*	-0.013	0.002	0.013		-0.009	-0.021	-0.009
	(0.021)	(0.040)	(0.023)	(0.021)	(0.021)		(0.020)	(0.021)	(0.020)
ln(*Patents stock*) $_{t-1}$	0.245**	0.184**	0.245**	0.240**	0.242**	0.047**	0.222**	0.218**	0.218**
	(0.018)	(0.050)	(0.024)	(0.019)	(0.018)	(0.016)	(0.017)	(0.019)	(0.018)
ln(*Sales*) $_{t-1}$	0.673**	0.634**	0.679**	0.691**	0.680**	0.602**	-0.271**	-0.257**	-0.265**
	(0.024)	(0.035)	(0.029)	(0.026)	(0.026)	(0.038)	(0.023)	(0.025)	(0.024)
Firm Fixed-effects	No	No	No	No	No	Yes	No	No	No
Four-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.835	0.745	0.860	0.843	0.840	0.954	0.680	0.688	0.685
Observations	10,954	4,110	6,844	9,606	10,153	10,885	10,954	9,604	10,151

Notes: This table reports the estimation results of the relation between R&D expenditure and decentralization. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. **, * denote significance levels of 1 and 5 percent, respectively.

Table 5. Patenting and Publishing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	*ln(1+Patents)*					*ln(1+Publications)*			
		Post-M&A Patents	Pre-M&A Patents	Exc. Outliers	Cites Weighed			Post-M&A Patents	Pre-M&A Patents
Share Decentralized $_{t-1}$	-0.195**	-0.236**	-0.187**	-0.182**	-0.224**	-0.172**	-0.118**	-0.069	-0.141**
	(0.058)	(0.068)	(0.064)	(0.059)	(0.056)	(0.049)	(0.047)	(0.054)	(0.052)
ln(1 + *No. Affiliates*)	0.090**	0.075**	0.085**	0.090**	0.096**	0.029	0.010	0.013	0.007
	(0.025)	(0.026)	(0.027)	(0.026)	(0.024)	(0.027)	(0.026)	(0.029)	(0.029)
ln(*R&D Stock*)$_{t-1}$	0.327**	0.325**	0.337**	0.272**	0.274**	0.167**	0.106**	0.107**	0.105**
	(0.024)	(0.026)	(0.026)	(0.018)	(0.022)	(0.022)	(0.020)	(0.021)	(0.022)
ln(*Sales*)$_{t-1}$	0.181**	0.213**	0.195**	0.203**	0.157**	0.140**	0.105**	0.109**	0.113**
	(0.020)	(0.023)	(0.022)	(0.020)	(0.020)	(0.019)	(0.017)	(0.019)	(0.019)
ln(1+*Patents stock*)$_{t-1}$							0.173**	0.189**	0.176**
							(0.021)	(0.023)	(0.022)
Four-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.627	0.652	0.643	0.607	0.587	0.468	0.499	0.522	0.509
Observations	15,764	13,578	14,387	15,203	15,764	15,764	15,764	13,578	14,387

Notes: This table reports the estimation results of the relation between patenting and publishing activity, and decentralization. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. **, * denote significance levels of 1 and 5 percent, respectively.

Table 6. Decentralization and Market Value

Dependent variable: ln(Market Value)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							Exc. Outliers	Post-M&A Patents	Pre-M&A Patents
ln(*Dec. Patents stock*)$_{t-1}$	0.091**	0.071**							
	(0.015)	(0.014)							
ln(*Cen. Patents stock*)$_{t-1}$	0.018	0.015							
	(0.014)	(0.013)							
Share Decentralized $_{t-1}$			0.217**	0.159**	0.155**		0.158**	0.141**	0.178**
			(0.052)	(0.048)	(0.049)		(0.049)	(0.055)	(0.052)
Dummy for Decentralized						0.157**			
						(0.044)			
ln(1 + *No. Affiliates*)		0.043**		0.043**	0.040*	0.031	0.040*	0.043**	0.035*
		(0.017)		(0.017)	(0.017)	(0.018)	(0.017)	(0.019)	(0.018)
ln(1+*Patents stock*)$_{t-1}$			0.057**	0.050**	0.058**	0.055**	0.060**	0.046**	0.053**
			(0.016)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ln(1+*Publications stock*)$_{t-1}$					-0.054**	-0.040*	-0.050**	-0.032*	-0.039*
					(0.018)	(0.018)	(0.019)	(0.018)	(0.017)
ln(*R&D stock*)$_{t-1}$	0.041*	0.026	0.039*	0.023	0.026	0.030	0.028	0.035*	0.033
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
R&D stock$_{t-1}$/Assets$_{t-1}$									
ln(*Assets*)$_{t-1}$	0.827**	0.452**	0.825**	0.447**	0.420**	0.441**	0.420**	0.438**	0.451**
	(0.019)	(0.031)	(0.019)	(0.031)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
ln(*Sales*)$_{t-1}$		0.413**		0.415**	0.466**	0.432**	0.465**	0.434**	0.418**
		(0.032)		(0.032)	(0.037)	(0.032)	(0.037)	(0.033)	(0.035)
Four-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.814	0.827	0.814	0.826	0.832	0.830	0.830	0.828	0.830
Observations	15,821	15,764	15,821	15,764	14,298	14,448	15,203	13,578	14,387

Notes: This table reports OLS estimation results of the effect of patent decentralization on firm market value. The level of analysis is firm-year. *Centralized* and *Decentralized* patents refer to whether they were assigned to an affiliate or headquarters, respectively. *Share Decentralized* divides a firm's total number of affiliate-assigned patents by its total number of patents. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. **, * denote significance levels of 1 and 5 percent, respectively.

Table 7. Sales Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: $\Delta\ln(Sales)_{t-1}$								
			Exc. Outliers	Post-M&A Patents	Pre-M&A Patents	Patents ≤ median	Patents > median	Two-Year Growth
Share Decentralized $_{t-1}$	0.037**	0.037**	0.037**	0.021*	0.040**	0.044**	0.029**	0.044**
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.015)	(0.012)	(0.015)
ln(1 + *No. Affiliates*)	0.021**	0.020**	0.021**	0.019**	0.019**	0.028**	0.019**	0.014**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
ln(*R&D Stock*)$_{t-1}$	0.010**	0.010**	0.010**	0.009*	0.009*	0.013**	0.016	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)	(0.007)
ln(1+*Patents stock*)$_{t-1}$	0.007*	0.007*	0.007*	0.008*	0.009**	-0.003	0.016**	0.018**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.009)	(0.006)	(0.005)
ln(1+*Publications stock*)$_{t-1}$		0.001						
		(0.003)						
ln(*Sales*)$_{t-1}$	-0.104**	-0.104**	-0.104**	-0.104**	-0.113**	-0.135**	-0.077*	0.093**
	(0.020)	(0.020)	(0.020)	(0.021)	(0.025)	(0.026)	(0.038)	(0.019)
ln(*Assets*)$_{t-1}$	0.056**	0.056**	0.057**	0.060**	0.066**	0.089**	0.017	-0.136**
	(0.018)	(0.018)	(0.018)	(0.020)	(0.022)	(0.026)	(0.027)	(0.019)
Four-digit SIC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.107	0.107	0.107	0.111	0.114	0.133	0.129	0.123
Observations	15,748	15,748	15,648	13,568	14,375	7,854	7,894	14,267

Notes: This table reports the OLS estimation results of the relation between of patent decentralization and firm sales growth. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. **, * denote significance levels of 1 and 5 percent, respectively.

TABLE 8. Diversity

	Dependent variable: ln(*Market Value*), OLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Specia-lized	Diver-sified					
Share Decentralized$_{t-1}$ × *Total Diversification*			0.011** (0.004)				
Share Decentralized$_{t-1}$ × *Unrelated Diversification*				0.140** (0.047)			
Share Decentralized$_{t-1}$ × *Related Diversification*					0.011** (0.005)		
Share Decentralized$_{t-1}$ × *Technical Concentration Index*						-0.245** (0.102)	
Share Decentralized$_{t-1}$ × *Geography Concentration Index*							-0.598** (0.191)
Share Decentralized$_{t-1}$	0.047 (0.112)	0.359** (0.086)	0.117** (0.057)	-0.096 (0.108)	0.139** (0.053)	0.251** (0.069)	0.277** (0.057)
Total Diversification			-0.003** (0.001)				
Unrelated Diversification				-0.081* (0.043)			
Related Diversification					-0.003** (0.001)		
Technology Concentration Index					-0.003** (0.001)	0.213 (0.140)	
Geography Concentration Index					-0.003** (0.001)		0.204 (0.129)
R^2	0.869	0.806	0.828	0.828	0.828	0.828	0.828
Observations	3933	3957	15,764	15,764	15,764	15,764	15,764

Notes: This table examines how the effect of decentralization on firm value varies with firms' technological diversity. *Total*, *Unrelated*, and *Related Diversification* are computed as the Entropy measure using patent IPC codes. Firms are classified as *specialized* (column 1) or *diversified* (column 2) based on the 1st and 4th quartile of *Total Diversification*, respectively. All regressions include the following additional controls: ln(*R&D Stock*), ln(*Assets*), ln(*Sales*), ln(1+ *No. Affiliates*), and complete sets of three-digit US SIC code and year dummies. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. **, * denote significance levels of 1 and 5 percent, respectively.