Exploration versus exploitation in technology firms: The role of compensation structure for R&D workforce

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A R T I C L E   I N F O

JEL classification: J310 O310 O320

Keywords: R&D employee Motivation Compensation Pay dispersion Tournament incentive Innovation Exploration and exploitation

A B S T R A C T

We investigate the relationship between a firm’s compensation structure and the extent to which its innovation is more exploration versus exploitation oriented. Specifically, we assess two aspects of a firm’s compensation design—horizontal dispersion within job levels and vertical tournament incentives between job levels. A six-year panel of compensation records of 671,028 employees working at 81 U.S.-based high technology firms between 1997 and 2002 is used to construct measures that characterize a firm’s pay structure, which are linked to these firms’ patents filed in the U.S. We find that firms with higher-powered tournament incentives in vertical compensation structure report higher fraction of innovation directed towards exploration. Horizontal pay dispersion, on the other hand, shows a negative relationship with the exploration in firms where R&D employees’ age variance is low. In firms where R&D employees’ age variance is high, the negative relationship between horizontal pay dispersion and exploration is muted.

1. Introduction

When do firms engage in more exploration- versus exploitation-oriented innovation? This question has drawn the interest of a large corpus of scholarly work and become one of the most intensively investigated areas in innovation research (Gupta et al., 2006; Lavie et al., 2010). For examples, research in this area has been fruitful in establishing how a firm’s exploration and exploitation are related to the distribution of resources such as absorptive capacity (e.g., Cohen and Levinthal, 1990; Hoang and Rothaermel, 2010; Rosenkopf and Nerkar, 2001; Rothaermel and Alexandre, 2009), organizational slack (e.g., Greve, 2007; Nohria and Gulati, 1996; Voss et al., 2008), alliance partners (e.g., Beckman et al., 2004; Lavie and Rosenkopf, 2006; Phelps, 2010; Rothaermel and Deeds, 2004), and experiences of the top management teams (e.g., Hambrick et al., 2005; Smith and Tushman, 2005).

In most of these studies, it’s a firm that reacts to the changes in the resource condition and adjusts its exploration and exploitation activities. While this approach has been successful in revealing critical strategic factors that shape firms’ exploration and exploitation, what’s been lost in most of the analysis is an understanding of what James March called “implicit choices...buried in many features of organizational forms and customs” (1991, p.71) and in particular the question regarding how these organizational practices are related to a firm’s exploration or exploitation.

Over the past decade or so, answers to this question above have started to trickle in, particularly around the role of organizational structure and design (e.g., Cszar, 2013; Fang et al., 2016; Jansen et al., 2006; Tushman et al., 2010) and innovation process management (Benner, 2002). However, there is still no empirical evidence of the link between a firm’s compensation design and its exploratory innovations. Sauermann (2017) suggested that individual motives matter for innovation outcomes. Among various types of organizational practices, there is no doubt a firm’s compensation ranks among the top in terms of its ability to shape the motives and activities of R&D employees and in turn the innovation outcome of the firm (Collins and Smith, 2006; Onishi, 2013). However, by far the limited amount of research on compensation and innovation (e.g., Balkin et al., 2000; Lerner and Wulf, 2007; Onishi, 2013; Yanadori and Cui, 2013) has largely treated exploratory and exploitative innovations as a collective bundle, thus failed to shed light on how compensation design may be differentially related to exploration and exploitation. As such, at this juncture, we...
may know the relationship of a given compensation design to a firm’s overall innovation performance, but there is not yet empirical inquiry regarding which type of innovation is produced in the firm given its compensation design. This, to us, is an important gap in the literature that needs to be addressed.

A second commonality across existing studies addressing compensation and innovation is that with the exception of Onishi (2013) and Yanadori and Cui (2013), previous empirical works examining compensation in firms almost exclusively focus on the compensation of senior leadership. While senior leadership makes strategic decisions regarding resource allocation, such singular emphasis on the top level of the firm misses the role played by lower-to-mid-tier employees and managers of the research and development (R&D) department, whose motives are intricately related to compensation design of the firm. For example, Onishi’s (2013) study based on a survey of Japanese firms reports that firms that link inventor compensation to patent performance see the development of more high-impact patents by their R&D employees though the number of patent applications is not impacted. This suggests that different compensation plan may be linked to employees’ strategic choice of what type of inventions to which they will devote more effort. We therefore seek to answer, in our paper, how a firm’s compensation design may be related to employees’ choice between exploratory and exploitative innovation projects, and consequentially the firm’s balance between exploration and exploitation.

The objective of this paper is to fill the gaps described above by assessing the relationship between a firm’s compensation design for the R&D workforce below executive level and its exploratory versus exploitative innovation performance. Given the space constraint, we focus on two specific aspects of compensation design, the horizontal pay dispersion and vertical tournament incentives in the compensation of the R&D workforce. Pay dispersion, defined as the extent to which compensation is differentiated among employees, has been recognized as one of the key decision areas in human resource management (Fredrickson et al., 2010; Kacperczyk and Balachandran, 2018; Shaw, 2014; Siegel and Hambrick, 2005). Tournament incentives have also been widely theorized as shaping employee activities (Lazear, 1989). We draw from theories on social comparison and tournament to motivate our empirical assessment. Specifically, we propose an explanation that builds on two defining characteristics of exploration: (i) they are highly risky in terms of success rate and possible returns and (ii) they often require combination of knowledge spanning multiple domains and as such collaboration of employees. Variations in firms’ horizontal pay dispersion and vertical tournament incentives design differently shape employees’ preferences with regard to risk-taking and collaboration. Consequentially, they are related distinctively to the level at which a firm’s innovation pivots toward exploration.

We empirically investigate these relationships in a novel dataset of 81 blue-chip U.S. high-tech firms with 671,028 person-year compensation records in their R&D divisions from 1997 to 2002. We use these anonymous HR data to construct measures that characterize firms’ compensation design. We then combine the compensation-structure measures with firms’ patent data obtained from the United States Patent and Trademark Office (USPTO). While there are limitations in our empirical approach, as we will note below, it is also worth highlighting the value of this dataset. It is extremely difficult for researchers to have access to HR data of a firm, let alone HR data of an entire division or entire firm. This partly explains the relative shortage of empirical evidence in innovation literature regarding properties of a firm’s compensation design. We are fortunate to have access to this dataset to take at least a first step to address the absence of research on compensation design and exploratory innovations and on the overall shortage of research on how activities of firms’ non-executive-level R&D workforce may be shaped by compensation design. There are also some limitations of our research to be noted up front. First, though we have complete HR records of each company, we are unable to match them to individual patenting activity due to anonymity of these records. This feature limits our ability to test hypotheses at the individual employee level. Second, causality identification is hard to establish in our empirical setting. The archival nature of our research design also makes it prone for endogeneity problems such as those arising from firms’ selective use of certain compensation designs. More importantly, it is notoriously difficult to time innovation projects. Though we observe when a patent application was filed, we cannot accurately determine whether the underlying project associated with the patent was initiated before or after a change in the firm’s compensation structure. This renders any match-sample based method for addressing selection problem ineffective for our empirical question. Indeed, this same problem was also encountered by other researchers using similar datasets (e.g., Lerner and Wulf, 2007, using executive level compensation data), who cautioned against causal interpretations of results based on similar archival data and research designs. Following these researchers, we interpret our results as showing only correlations between pay dispersion and patterns of innovation in a firm. Weakness notwithstanding, given the absence of empirical evidence on compensation and exploratory/exploitative innovation, particularly at the non-executive level where our focus is, we see the value of at least revealing the correlation to interested scholars to trigger future effort in better establishing the causality in any observed relationship.

The rest of the paper is organized as below: Section 2 motivates our focus on corporate R&D employees; in Section 3 we develop our hypotheses regarding horizontal and vertical compensation design and a firm’s exploratory innovation; Section 4 describes our data and methodology; Section 5 reports our results and robustness checks; Section 6 discusses and concludes.

2. Non-executive level R&D employees and firm innovation

Among the small number of existing investigations that empirically document the relationship between corporate compensation design and general innovation outcomes, most of the attention has been devoted to occupants of high-level positions such as CEOs (e.g., Balkin et al., 2000), heads of central R&D organizations (Lerner and Wulf, 2007), or divisional CEOs (Dechow and Sloan, 1991; Holthausen et al., 1995). The focus on the high-level corporate officers may be largely driven by the consideration that these officers are responsible for allocating resource across different research projects, hence potentially shape the directions of research and innovation outcomes in a firm.

While we agree that senior executive officers play an important role in a firm’s innovation, we choose to focus on the R&D employees at the non-executive level, which are largely missing in previous research. This naturally leads to the question regarding the role played by these non-executive level employees in corporate innovations. In assessing this question, we consider four recent trends of development in corporate R&D, which lead us to believe that activities of rank-and-file R&D employees play a non-negligible role in driving the innovation patterns of a firm.

First, beginning in the late 1980s, industrial research in the U.S. has become more decentralized. Firms increasingly shunned centralized R&D in favor of a divisional research structure in which decisions on research are no longer limited to the corporate headquarter (Rosenbloom and Spencer, 1996). For example, Lerner and Wulf (2007) found that financial incentives to heads of corporate R&D bear no relationship with innovation performance in firms that have divisional R&D departments. These findings suggest to us the need for more research effort beyond the level of top executive team when trying to explain how incentives are related to innovation outcomes.

Second, the past three decades also saw firms becoming less hierarchical and more flexible in structure and management. For example, in an in-depth case study, Nonaka (1988) reported Honda’s use of a “middle-up-down” approach in its development of Honda “City”, a new car model. In this approach, the new car development project was
initiated from the mid-level of the firm as opposed to the executive level in the conventional decision process of new model development. More recently, there has been both anecdotal documentations and academic studies of firms’ use of lab-like, small project teams as the basic unit of corporate research (e.g., Bock, 2015; Liu and Stuart, 2015). Such a structure is much flatter and more flexible than in traditional organizational hierarchy, and decision rights are more dispersed among middle to lower level employees. Research has also found that managing the tension between exploration and exploitation in innovation process has become a shared responsibility across organizational levels, not that of top management (Andriopoulos and Lewis, 2009). Given these changes, it is no longer accurate to assume that rank-and-file employees are merely passive participants of the R&D process in a firm.

The third noticeable trend is the diffusion of the discretionary time practice, particularly for R&D employees. In companies such as 3 M and Google, engineers are allowed to devote a fraction of their time at work to projects of their own choosing, even if the projects are not directly related to any immediate corporate goals (Battelle, 2006). This implies that setting research direction is no longer the sole responsibility of top executives and that the preferences of mid-to-lower level research personnel to some extent drive the type of innovations being generated by a firm. Together, these trends suggest an expanding role in knowledge creation played by R&D employees below the senior ranks, as they gain more autonomy in today’s organizations.

Furthermore, as we have summarized in the introduction section, two recent studies by Onishi (2013) and Yanadori and Cui (2013) report a relationship between how non-executive R&D personnel are paid and the performance of innovations in the organization. The combination of such evidence from academic studies and trends reported in practitioners’ accounts leads us to believe that at a minimum, whether or not non-executive R&D personnel may play a role in a firm's innovation pattern should be treated as a question that deserves empirical investigations.

3. Hypotheses

3.1. Risks, collaboration and exploratory innovation

The terms of exploration and exploitation have been invoked in prior literature to explain a host of firm activities and outcomes at various levels of analysis (Gupta et al., 2006; Lavie et al., 2010). In our paper, we use the terms to explain how firms manage and generate new knowledge. For this purpose, we are largely using the framework established in March (1991) and further by Levinthal and March (1993): within the knowledge management domain, exploration-oriented innovation often involves experimentation, distal search, and variation from existing knowledge base. Exploitation-oriented innovation, on the other hand, is often associated with implementation and refinement of existing knowledge, local search, and variation reduction.

Existing literature highlights two defining characteristics of exploratory innovations that further differentiate them from exploitative innovations. The first is what March termed the “vulnerability of exploration” (1991, p.73). Exploratory innovation breaks into new knowledge domain in which the firm has not traveled before. It might involve new methods or equipment, or new ways of combining ideas. As such, exploratory R&D process is known to be full of risks and uncertainties. In the process of achieving such corporate innovations, there are also many factors that are out of the control of R&D employees (Ahuja et al., 2008). Sometimes, serendipity plays a role in the production of exploratory innovation, as in the invention of drugs from penicillin to Viagra. As such, “vulnerability of exploration” has two implications: (1) as exploratory innovation is inherently uncertain with regard to its probability of success, yield time, and even what production inputs contribute to project success, it is challenging for a firm to adequately measure employee contribution to exploratory innovation; (2) exploratory innovation requires a relatively high level of risk tolerance from employees.

Second, previous literature has also noted the recombinant nature of exploratory innovation. One key insight from existing work (March, 1991; Rosenkopf and Nerker, 2001) is that heterogeneity in a firm’s knowledge stock influences the trajectory of exploratory innovation. Recall from March’s (1991) definition that exploratory innovation requires experimenting and differentiating from existing stock of knowledge and familiar ways of problem solving. Using simulation models, March (1991) showed that an increase in knowledge heterogeneity across organizational members, whether through differences in the rate of learning or employee mobility, facilitates the development of exploratory innovation in the organization. Rosenkopf and Nerker (2001) further showed that the quality of exploratory innovation is associated with the extent to which the innovation draws from multiple knowledge domains, i.e., spanning knowledge boundaries. The more an exploratory innovation draws knowledge from knowledge that spans heterogeneous domains, the higher the value of the exploratory innovation. Similar pattern is found in a recent analysis of a large sample of patent innovations (Corredoira and Banerjee, 2015). While recombination of heterogeneous, cross-boundary knowledge is valuable for the production of exploratory innovation, most people have expertise of a relatively narrow domain of knowledge. This implies that work interdependence is high in exploratory innovation context. To generate exploratory innovations, employees who possess heterogeneous knowledge will likely need to collaborate to make the knowledge recombination feasible. For this reason, whether or not employees can effectively collaborate with each other can be considered a determinant factor of a firm’s exploratory innovation performance (Siggelkow and Rivkin, 2006).

To summarize, compared to exploitation, exploration-oriented innovation projects will bear the following characteristics: (i) they are associated with a higher level of risks and uncertainty of success, and (ii) they are more dependent on collaborations.

3.2. Horizontal pay dispersion, social comparison and exploration

We first turn to horizontal pay dispersion, which is defined as the difference of compensation among employees at the same job level (Siegel and Hambrick, 2005; Gupta et al., 2012). When firms adopt a compensation design that emphasizes horizontal pay dispersion, it is believed that they are trying to mimic a more market-like incentive structure that is effective at motivating social comparison across employees (Nickerson and Zenger, 2008). To the extent that such social comparison intensifies a sense of competition among employees to win the rewards, a high-dispersion structure may have a positive relationship with employee motivation (Gerhart and Rynes, 2003; Treviño et al., 2012). Prior theorization, however, is unclear about where the enhanced employee effort will be directed. Assuming dispersion motivates more effort, will R&D employees be motivated to direct more effort to exploratory innovation projects or otherwise (to more exploitative innovations)?

We argue that the (positive) motivational effect of horizontal pay

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2 The chemical compounds for Viagra were originally investigated by Pfizer scientists to treat cardiovascular diseases. In the clinical trials, Pfizer scientists found that the compounds have no significant effect on the target cardiovascular disease. By accident, however, scientists found that the compounds can improve erectile dysfunction, thus leading to the final success of Viagra (Ban, 2006).
dispersion is less likely to happen in the context of exploratory innovations than in the context of exploitation-oriented innovations. This is because there is an important premise underlying the positive performance effect of pay dispersion—the dispersion-creation practice needs to be perceived as legitimate by the employees. In the eyes of employees, the pay differential needs to be well explained by performance and performance needs to be convincingly measured (e.g., in a context such as professional hockey used in Trevor et al. (2012)). This is easier to achieve in the management of exploitation-type innovations but will be a challenge in the management of exploration-type innovations. As discussed in the proceeding section, exploratory innovation research is characterized by a high degree of uncertainty in the probability of success and the timing of success. Such features imply tremendous challenge in measuring employee productivity in a convincing way. Challenges also abound in establishing a legitimate link between productivity input measure and employee performance and further in justifying pay variation in exploratory innovation. As such, the proportion of pay variation that can be legitimately explained by objective and convincing productivity measure will be relatively small in the context of exploratory innovation. In contrast, in managing exploitation-type innovation projects, firms are more likely to develop convincing evaluation metrics and reward schema given the more predictable features of such innovations. As such, if horizontal pay dispersion can motivate employee effort, it is more likely to be effective in motivating exploitation than exploration-type of projects.

On the other hand, Nickerson and Zenger (2008) suggest that envy may be the cost of social comparison in a more market-like compensation design. The higher level of pay dispersion may encourage employees to view compensation at work as a zero-sum game and react negatively with dysfunctional behaviors such as withdrawal of cooperation (Pfeffer and Langton, 1993). For example, Shaw et al. (2002) report that horizontal pay dispersion is positively associated with employee performance when the work is more independent. In contrast, when the relevant work is interdependent, which implies more dependency on collaboration across employees, high level of pay dispersion may be an ineffective vehicle for improving employee performance. Such findings have important implications for our interest in the link between compensation design and the type of (exploratory or exploitative) innovations. As discussed in the proceeding section on features of exploratory innovation, collaboration is important due to the knowledge re-combinatory nature of exploratory innovation (Sigellkow and Rivkin, 2006). Existing empirical research so far has been relatively consistent in the negative effect of large horizontal pay dispersion on employee collaboration in highly interdependent work context (e.g., Bloom, 1999; Fredrickson et al., 2010; Pfeffer and Langton, 1993; Shaw et al., 2002; Siegel and Hambrick, 2005). Taken together, these studies suggest that the social comparison cost may lead to less cooperation across employees, which may negatively impact exploratory innovation projects. We expect that:

Hypothesis 1. The extent of a firm’s exploratory innovation is negatively related to the level of its horizontal pay dispersion in the R&D department.

3.3. Vertical tournament structure and exploratory innovation

A firm’s pay dispersion can also be characterized along the vertical dimension, which captures the pattern of pay variation across job levels of a firm. The mechanisms that drive the effect of vertical pay structure on performance are likely somewhat different from those underlying horizontal pay dispersion. Most notably, while social comparison matters greatly in horizontal pay dispersion, this mechanism is expected to play a lesser role in the consideration of vertical pay structure (Bloom, 1999; Gupta et al., 2012). This is because in vertical pay structure, the concerned employees are at different levels of a firm and their jobs are likely to be different from each other, which renders cross-level comparison less obvious.

In a typical firm, lower level employees compete for the opportunity of promotion into a higher-level job and correspondingly a higher level of compensation post-promotion. By far, there has been a steady stream of empirical works supporting the characterization of a corporate pay hierarchy as following a tournament structure (Cappelli and Cascio, 1991; Conyon et al., 2001; Devaro, 2006; Eriksson, 1999; Kale et al., 2009; Lambert et al., 1993; Main et al., 1993). For this reason, research on the vertical pay structure of a firm often invokes the tournament theory (Laazaar and Rosen, 1981) in the explanation of the relationship between vertical pay structure and organizational performance (Gupta et al., 2012).

The main insight from the classic tournament theory (Laazaar and Rosen, 1981) is that organizations use high-powered incentives to motivate the effort of aspiring employees (tournament participants). Existing research points to two consequences of tournament incentives that we believe are relevant to the process of exploratory innovation. First, as we discussed earlier, exploratory innovation is characterized by a high degree of risk and uncertainty in outcomes. Consequentially, employees who engage in exploratory projects are effectively taking on more risks in terms of reward to their effort. From the tournament research, there is empirical evidence that suggests individuals who are motivated by high-powered tournament incentives are likely to take on more risks. For example, Becker and Huselid (1992) study NASCAR races and find that as prize spread increases, contestants are taking on more risks in their bid for the final win. In the context of management, Kini and Williams (2012) find a positive relationship between vertical pay difference within a firm and the strategic risks taken on by a firm (or implicitly, taken on by the firm’s CEO or executive officers). We draw from these studies and postulate that in firms with higher-powered tournament incentives in its vertical pay structure, employees aspiring after the top jobs may be more willing to take on the riskier exploratory projects.

The way that tournament incentives may work in shaping individual choice of the type of innovation is also consistent with the theory proposed in research by Manso (2011) and Azoulay et al. (2011). An important part of the theory advanced in the two papers is that an incentive design that (i) tolerates early-stage failure and (ii) allows adequate time horizon for innovation projects to bear fruits may effectively promote more radical, exploratory innovations. In a more high-powered tournament scheme, rewards for moving up an organizational ladder often follow a more convex structure: i.e., the rate of pay increase is larger at the higher levels in the vertical compensation structure than at the lower levels. This implies that for a lower and mid-tiered employee, the penalty for losing a promotion competition in the near term is smaller. For these employees, because the big payoff is near the top of the organizational pay structure, which happens further down the road rather than immediately, there are incentives for them to take more risks with innovation projects in order to achieve a bigger bang in the long run.3

There are, however, reasons for suspecting that a high-powered tournament incentive structure may direct employee effort away from exploratory innovation. Recall from the previous section, exploratory innovation benefits from collaboration of employees. For this reason, the way a tournament pay structure affects collaboration will have negative implications for the exploratory innovation effort as well as success rate of exploratory innovation projects. In tournaments, winning is contingent on relative rather than absolute performance. This means that a tournament contestant can win by either better performance on his/her own, or worse performance of his/her competitors (Laazaar, 1989). As such, it is possible that the stronger the tournament incentives, the more likely the contestants may resort to sabotaging

3 We appreciate the help from one of the reviewers who brought to our attention this long- vs. short-term perspective in compensation design proposed in Manso’s (2011) research.
colleagues as a strategy to win. In particular, a large tournament prize is expected to be negatively associated with the degree of collaboration among contestants for the prize (Dye, 1984). For example, Siegel and Hambrick (2005) find that the negative effect of tournament incentives on firm performance is stronger in industries that require more collaboration among executive team members. Cowherd and Levine (1992) find that a smaller pay gap between lower-echelon employees and upper-echelon managers contributes to higher product quality by increasing lower-echelon employees’ commitment and cooperation.

Taken together, there exist two opposing mechanisms that underlie the relationship between the extent of tournament incentives in vertical pay structure and the extent that a firm’s innovation is directed towards exploration. On the one hand, a high degree of tournament incentives in vertical pay structure may increase employee risk tolerance, which creates stronger incentives for employee effort into exploratory rather than exploitative innovation. On the other hand, anti-collaborative tendency increases among employees along with the degree of tournament incentives. Short of collaboration across employees, exploratory innovations often face a higher likelihood of failure than exploitation-oriented innovations. These considerations lead us to the following competing hypotheses:

**Hypothesis 2a.** The extent of a firm’s exploratory innovation is positively related to the degree of tournament incentives in its vertical pay structure of the R&D department.

**Hypothesis 2b.** The extent of a firm’s exploratory innovation is negatively related to the degree of tournament incentives in its vertical pay structure of the R&D department.

### 4. Method

#### 4.1. Data and Sample

To assess the relationship between compensation structure and the balance of exploratory innovation in firms, we use an annual compensation survey administered by a Boston-based major HR consulting firm to the U.S. high-technology (mainly information technology) firms. Participating firms supply the consulting firm with information on each of their employees’ compensation packages, and in return are provided with market pay information for benchmarking. We were granted access to the data that span a six-year period from 1997 to 2002. We restricted our sample to the R&D divisions of 81 publicly traded firms in the dataset, which includes over 671,028 person-year compensation records during this period of time. The final dataset we analyze is an unbalanced panel structure of 381 firm-year observations. Industrial breakdown and financial characteristics of the sampled firms are summarized in Tables 1 and 2.

This dataset attracts us for several reasons. First, the majority of existing compensation studies use publically available compensation information on senior executives or players in sports. Corporate compensation data are very difficult to come by. That partly explains a general shortage of empirical tests of compensation theories with longitudinal firm data. In particular, corporate technological innovation as a highly interdependent context for testing some of the existing compensation theories has rarely been used in previous works (Onishi (2013) and Yanadori and Cui (2013) are exceptions) and empirically-based assessment of compensation design’s link to the type of innovation being generated in firms is largely missing in the innovation literature. This dataset provides us an opportunity to fill this gap.

Second, among existing studies on pay dispersion, only a few have explicitly examined vertical pay structure (Gupta et al., 2012; Kacperczyk and Balachandran, 2018). We suspect that one reason for a lack of empirical examination of vertical structure is that to adequately measure vertical structure, researchers need to have a scheme that categorizes employee pay by administrative levels in a relatively consistent way across sampled firms to ensure comparability of the vertical structure measure across firms. This is extremely difficult at the below-executive level as firms vary greatly in their way of organizing administrative categories and titles. The advantage of this dataset is that the HR consulting firm has created a common categorization scheme that has been used relatively consistently across firms and years. In administering the employee compensation survey to the participating firms, the consulting firm provided detailed instructions (e.g., specific responsibilities, required experience, etc.) for the participating firms’ HR managers to categorize jobs in the R&D department into eight levels: three top levels for managers and five lower levels for non-managers. Though unfortunately we were not provided with the details of these categories, we have reasons for trusting the reliability of the data. The goal of these surveys is to pool compensation information from firms to construct useful benchmarks for their HR managers. The consulting firm that conducted these surveys specializes in HR and compensation issues and it has historically been working closely with the participating firms. In addition, there is strong incentive for the HR managers of the participating firms to ensure that the reporting and categorization of their employee compensation information are accurate and consistent with the requirement of the consulting firm, as failure to do so will distort the compensation benchmarks that they are seeking from the consulting firm. This feature of the data turns out to be truly instrumental for us to obtain reliable measures to characterize firms’ horizontal and vertical pay structure.

Admittedly, ours is not a randomly selected sample and for this reason we should caution over-interpretation of our findings. Nevertheless, systematic, large-scale employee-level compensation information is difficult to come by, particularly at the non-executive levels that we analyze. For this reason, previous researchers who studied compensation below the senior executive ranks often resort to similar, consulting-based proprietary datasets as in our case (e.g., Bloom and Michel, 2002; Lambert et al., 1993; Lerner and Wulf, 2007; Main et al., 1993; Siegel and Hambrick, 2005; Yanadori and Cui, 2013; Yanadori and Marler, 2006).

#### 4.2. Variables

Variable definition and descriptive statistics are provided in Tables 3 and 4, and correlation matrix is provided in Table 5. We also tested for multicollinearity with VIF scores for all of the models and none of

<table>
<thead>
<tr>
<th>Table 1 Characteristics of sampled firms.</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of employees (in 1000)</td>
<td>59.58</td>
<td>67.72</td>
<td>0.175</td>
<td>337.9</td>
</tr>
<tr>
<td>Research and development expenses (in $mm)</td>
<td>977.8</td>
<td>1,198</td>
<td>7.526</td>
<td>5,152</td>
</tr>
<tr>
<td>Sales/turnover (net) (in $mm)</td>
<td>13,631</td>
<td>16,309</td>
<td>46.63</td>
<td>88,396</td>
</tr>
<tr>
<td>Net income (loss) (in $mm)</td>
<td>384.0</td>
<td>3,737</td>
<td>−56,121</td>
<td>10,535</td>
</tr>
<tr>
<td>Total assets (in $mm)</td>
<td>18,079</td>
<td>24,891</td>
<td>41.60</td>
<td>289,760</td>
</tr>
<tr>
<td>Total current assets (in $mm)</td>
<td>7,207</td>
<td>8,978</td>
<td>29.99</td>
<td>55,790</td>
</tr>
<tr>
<td>Total current liabilities (in $mm)</td>
<td>5,092</td>
<td>6,889</td>
<td>10.93</td>
<td>39,578</td>
</tr>
</tbody>
</table>
We have also experimented with other windows (e.g., seven years) and our empirical results are not sensitive to our choice of repeat-cite window. This holds for both proportion of exploratory citations and proportion of exploratory patents.

The maximum VIFs exceeds the conventional cutoff value of 10 (Ryan, 1997).

Dependent Variables. Following previous research (e.g., Balkin et al., 2000; Lerner and Wulf, 2007), we rely on patents as indicators of innovation. Firms in our data on average were granted 309 patents in a year by USPTO. Such a high level of patent count per firm reassures us that patenting is a primary vehicle for protecting innovations and is indicative of the innovation patterns in these firms.

We use four different measures of the extent that a firm’s innovation is directed towards exploration. First, we follow Phelps (2010) and compute the proportion of exploratory citations reflected in the patents filed by a firm in a given year. Specifically, we took all successful patent applications filed by a firm in the given year and examined all the backward citations made in those patents to relevant prior art. Among these backward citations, we define new citations as those that are neither self-cites (i.e., citations to the firm’s own patents filed prior to the given year), nor repeat cites (i.e., citations to patents that the firm has previously cited in the past five years). [Reference: Phelps (2010)]

Table 2

<table>
<thead>
<tr>
<th>SIC category name (code) breakdown of sampled firms</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrial and commercial machinery and computer equipment (35)</td>
<td>17</td>
<td>21.0</td>
</tr>
<tr>
<td>Electronic and other electrical equipment and components, except computer equipment (36)</td>
<td>31</td>
<td>38.3</td>
</tr>
<tr>
<td>Transportation equipment (37)</td>
<td>4</td>
<td>4.9</td>
</tr>
<tr>
<td>Measuring, analyzing, and controlling instruments; photographic, medical and optical goods; watches and clocks (38)</td>
<td>14</td>
<td>17.3</td>
</tr>
<tr>
<td>Communication (48)</td>
<td>2</td>
<td>2.5</td>
</tr>
<tr>
<td>Business services (73)</td>
<td>13</td>
<td>16.0</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Variable definition</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of exploratory citations</td>
<td>Proportion of new backward citations to total number of backward citations in the patent applications filed by the firm in a given year. New citations are defined as those that are neither self cites (i.e., citations to the firms’ own patents filed prior to the given year), nor repeat cites (i.e., citations to patents that the firm has previously cited in the past five years). [Reference: Phelps (2010)]</td>
</tr>
<tr>
<td>Proportion of exploratory patents</td>
<td>Proportion of exploratory patents to total number of patent applications filed by the firm in a given year. Exploratory patents are defined as those that neither self-cite nor repeat-cite. [Reference: Sorensen and Stuart (2000); Benner and Tushman (2003)]</td>
</tr>
<tr>
<td>Originality</td>
<td>For each patent filed by a firm in a given year, originality of patent is ( 1 - \frac{\sum_{i=1}^{n} s_i}{\sum_{j=1}^{m} s_j} ) where ( s_i ) is percentage of backward citations made by patent ( i ) to patent class ( j ) out of ( n ) patent classes (the reverse of Herfindahl concentration index). The originality measure for a firm in a given year is the mean originality of all patents filed by the firm in the year. [Reference: Trajtenberg et al. (1997)]</td>
</tr>
<tr>
<td>Technology proximity</td>
<td>Compares the distribution of all patents filed by a firm in a given year across patent classes to the distribution of its patents filed in the previous five years across patent classes; the measure is computed as cosine similarity in the distributions of patents across technology classes (USPTO patent classes) between current and past five years; a larger technology proximity value indicates a firm’s innovations are more similar to those generated from the previous period, thus less exploratory. [Reference: Jaffe (1986).]</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>The average of the coefficients of variation for each of the job levels in the firm’s R&amp;D divisions. The coefficient of variation for a job level in the firm’s R&amp;D divisions is the standard deviation of all employees’ pay packages at that level divided by the mean of all employees’ pay packages at the level.</td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td>The ratio of upper-job-level percentage differential to the ratio of lower-job-level percentage differential. The upper-job-level percentage differential is the percentage difference between the average of highest ranked managers (job level 8) and the average of highest ranked non-managerial employees (job level 5). The lower-job-level percentage differential is the percentage difference between the average of the highest ranked non-managerial employees (job level 5) and the average of the entry-level non-managerial employees (job level 1), all within the R&amp;D divisions of the firm.</td>
</tr>
<tr>
<td>Average employee age</td>
<td>The average age of all employees in the firm’s R&amp;D divisions</td>
</tr>
<tr>
<td>Std. dev. of employee age</td>
<td>The standard deviation of age of all employees in the firm’s R&amp;D divisions</td>
</tr>
<tr>
<td>Firm size</td>
<td>Log number of employees in the entire firm</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>The ratio of R&amp;D expenditure to firm sales</td>
</tr>
<tr>
<td>Financial slack</td>
<td>The current ratio of the firm (current assets divided by current activities)</td>
</tr>
<tr>
<td>Past five-yr. exploratory patent ratio</td>
<td>Ratio of exploratory patent applications filed by the firm in the past five years</td>
</tr>
<tr>
<td>Pay level</td>
<td>Average pay of all R&amp;D employees in the firm, divided by CPI of that year</td>
</tr>
<tr>
<td>Industry</td>
<td>2-digit SIC industry categories</td>
</tr>
<tr>
<td>Year</td>
<td>Calendar year</td>
</tr>
</tbody>
</table>

Our second measure, proportion of exploratory patents follows a similar construction as our first, citation-based measure. In this one, we take all patents filed by the firm in a given year, and classify those patents as exploratory if they have neither self-cite nor repeat-cite previous patents in the defined window. This measure is then computed as the proportion of exploratory patents among all patents filed by the firm in the year. This measure is also widely used in previous works on exploratory innovations (e.g., Benner and Tushman, 2003; Sorensen and Stuart, 2000).

Our third exploration indicator is the average originality (Trajtenberg et al., 1997) of a firm’s patents filed in a given year. Patent originality measures the extent a firm’s patents cite prior patents in a wide range of patent technology classes. The more concentrated a firm’s patent citations are in a small number of patent classes, the less original its patents. More original patents are in general more likely to break new paths for future innovations. As such these patents are exploratory in nature (Rosenkopf and Nerkar, 2001).

Fourth, we have adapted Jaffe’s (1986) patent-class-based technology proximity measure to gauge the extent of technology exploration of our sampled firms. For a given firm, we collect the distribution of its patents filed in a given year. We compute technology proximity as the cosine similarity in the patent-class distribution of the firm’s patents filed in that year and the patent-class distribution of all patents filed by the firm in the previous five years. Essentially, this measure captures the extent that a firm’s innovation shifts away from its previously occupied patent classes. The larger the technology proximity value, the
more similar the firm’s innovations to that of a previous period, and the less exploration reflected in the firm’s new patent filings. As such, the coefficient estimates on technology proximity are expected to run in the opposite direction as the estimates for the other three exploration indicators.

To summarize, we use four different variables to measure exploration. While all these measures are constructed to capture the extent of path-breaking and boundary-spanning in patent innovations, they also focus on different aspects of exploration. The first three measures are better at capturing exploration based on the amount of novel knowledge elements upon which an innovation is built while the fourth measure, technology proximity, focuses more on shifts in the technology portfolio of a firm across technological (patent-class) boundaries.

Independent Variables. For horizontal pay dispersion, we follow prior studies (e.g., Fredrickson et al., 2010) and use the coefficient of variation, which is the standard deviation of the total pay packages of employees divided by the mean of employee total pay packages. We calculate the coefficient of variation for each of the job levels in a firm’s R&D division and then average them across all job levels to get horizontal pay dispersion for the firm.

We compute two indicators of a firm’s vertical pay structure. First, we follow Siegel and Hambrick’s (2005) measure to gauge the extent to which a vertical tournament incentive scheme exists in the R&D division. We first compute the percentage differential in pay between the average of the highest-ranked non-managerial R&D managers (job level 8) and the average of the highest-ranked non-managerial R&D employees (job level 5). Then, we divided this term by the percentage increase of the lowest level of compensation (level 1). For example, if the average level-8 manager receives $200,000 and the average level-5 non-manager receives $100,000, and the average level-1 non-manager receives $60,000, the vertical tournament incentive score is measured as:

\[
\frac{(200,000 - 100,000)/100,000}{(100,000 - 60,000)/60,000} = 1.5
\]

Equation 1.5

Essentially, this measure captures the extent at which the rate of senior-rank compensation increase (levels 5–8, reflected in the numerator of the equation) outpaces the rate of junior-rank compensation increase (levels 1–5, reflected in the denominator of the equation). The larger the ratio, the more increase one gets as he/she moves up the ladder of the firm’s pay hierarchy, reflecting a higher degree of tournament incentives within the firm.5

The second indicator is vertical pay differential, which measures the percentage difference between the highest level (level 8) of compensation to the lowest level of compensation (level 1). For example, if the average level-8 manager receives $200,000 and the average level-1 non-manager receives $60,000, the vertical pay differential score is 2.33 = ([200,000 – 60,000]/60,000).

These two indicators measure different aspects of the vertical pay structure in a firm. Vertical pay differential captures the gap between the highest and the lowest level of compensation of a firm. It does not, however, capture the shape of compensation change as an employee moves up a firm’s hierarchical ladder. Hypothetically, the shape of compensation change along organizational hierarchy can follow a linear function, in which the proportional increase in pay is uniform as an employee ascends the firm’s hierarchy. Alternatively, it can follow a concave function if the initial rate of increase at the lower levels of a hierarchy is larger than the pace of increase at the higher levels. The opposite case would be a convex shape if the rate of increase at the relatively lower levels is smaller than the rate of increase at the higher levels. Such a difference in the rate of compensation increase in vertical ascendency of organizational hierarchy is a better indicator of the tournament nature in a firm’s vertical pay structure—whether or not the firm is creating higher-powered incentives as promotions get closer to the pinnacle of the organizational hierarchy. This aspect of vertical pay structure is captured by vertical tournament incentive.

Control Variables. Prior research has guided our choice of control variables. First, following Ahuja (2000) and Katila and Chen (2008), we control for firm size with the log of the number of employees in the entire firm. Second, we include as a control R&D intensity of the firm, which is measured by the ratio of R&D expenditure to sales (Hall and Ziedonis, 2001). Third, we control for firms’ financial slack because it may affect the investment patterns in R&D (Nohria and Gulati, 1996). Financial slack is measured using a firm’s current ratio (i.e., current assets divided by current liabilities) following Wang et al. (2009). Fourth, we control for firm innovation path with its past five-year exploratory patent ratio, i.e., the percentage of exploratory patents among all patents that were successfully granted to the firm in the past five years. The five-year window is chosen because knowledge depreciates quickly in high-technology firms (Argote, 1999). Fifth, we control for R&D employees’ average pay level, which is likely to be associated with their innovation productivity (Yanadori and Cui, 2013). We measure pay level by calculating the average pay of all R&D employees in the firm, normalized by consumer price index of the year (Fredrickson et al., 2010). In an unreported robustness test, we also used the alternative measure of average pay of the middle-level (level 4) of the firm and obtained similar results. Sixth, we also generate two employee age-related variables—the average employee age and the standard deviation of employee age in the firm’s R&D division for assessing the influence of employee age demographics. Finally, to account for unobserved factors associated with the conditions of a specific year or industry, we include in all models year dummies as well as two-digit SIC industry dummies.
5. Results

We report, in Tables 6a–6d, four sets of analyses that relate pay structure to the different measures of firms’ exploratory innovation. Table 6a reports fractional logit regression of explanatory variables on firms’ proportion of exploratory citations. In model 1, we estimate the baseline model with all control variables included. This model as well as other models in the Table 6 series also control for industry and calendar year fixed-effects. Among all control variables, a firm’s past 5-year exploratory patent ratio, which measures the firm’s exploratory innovation track record as reflected in patents, stands out as highly correlated with the firm’s current year exploratory citation proportion. This is consistent with prior literature that suggests patterns of firms’ innovations are highly path-dependent. Taken together the baseline estimates of the set of control variables on all four dependent variables (in model 1 of Tables 6a–6d), it appears that this measure of a firm’s past track record of exploration is the only one that is consistently related to all four indicators of exploration. The other variables, firm size, financial slack, R&D intensity and firm employee demographic profiles, are related to some indicators of exploration but not others.

Model 2 adds horizontal pay dispersion. We do not observe a statistically significant relationship between horizontal pay dispersion and the firm’s proportion of exploratory citations. However, in the next section of “Scope Condition for Horizontal Pay Dispersion”, we further investigate this question and reveal that under certain scope conditions, this hypothesized relationship may still exist. More details are in the next section.

In model 3, we introduce vertical pay differential. This measure captures the gap between the top and the bottom of a firm’s pay hierarchy. A larger vertical pay differential indicates the firm’s compensation spread is large between top and bottom levels. The estimate is positive, though with weak statistical significance at p < 0.1. A standard deviation increase in vertical pay differential of a firm is associated with 10.8 percent (=exp[1.732*0.059]) increase in the proportion in exploratory citations in the firm’s patents.

In model 4, we introduce vertical tournament incentives, which captures the shape of pay increase as an employee moves up a firm’s
### Table 6a
Fractional logit regressions on proportion of exploratory citations.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td>Constant</td>
<td>−1.300</td>
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<td>−1.246</td>
<td>−1.527</td>
<td>−1.456</td>
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<td>(0.820)</td>
<td>(0.821)</td>
<td>(0.820)</td>
<td>(0.832)</td>
<td>(0.833)</td>
<td>(1.072)</td>
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<td>Firm size</td>
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<td>(0.036)</td>
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<tr>
<td>R&amp;D intensity</td>
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<td>−0.499</td>
<td>−0.528</td>
<td>−0.514</td>
<td>−0.578</td>
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<td>(0.383)</td>
<td>(0.382)</td>
<td>(0.385)</td>
<td>(0.386)</td>
<td>(0.382)</td>
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<td>Financial slack</td>
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<td>0.039</td>
<td>0.028</td>
<td>0.045</td>
<td>0.034</td>
<td>0.046</td>
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<td>(0.048)</td>
<td>(0.049)</td>
<td>(0.049)</td>
<td>(0.049)</td>
<td>(0.049)</td>
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</tr>
<tr>
<td>Past 5-yr exploratory patent ratio (lagged by 1yr)</td>
<td>2.714</td>
<td>2.723</td>
<td>2.780</td>
<td>2.711</td>
<td>2.759</td>
<td>2.757</td>
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<td>(0.221)</td>
<td>(0.223)</td>
<td>(0.222)</td>
<td>(0.226)</td>
<td>(0.223)</td>
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<tr>
<td>Pay level</td>
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<td>−0.170</td>
<td>−0.259</td>
<td>−0.007</td>
<td>−0.201</td>
<td>−0.117</td>
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<td>(0.182)</td>
<td>(0.231)</td>
<td>(0.212)</td>
<td>(0.184)</td>
<td>(0.248)</td>
<td>(0.246)</td>
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<td>Average employee age</td>
<td>−0.063</td>
<td>−0.054</td>
<td>−0.079</td>
<td>−0.050</td>
<td>−0.059</td>
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<td>(0.215)</td>
<td>(0.215)</td>
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<td>(0.218)</td>
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<td>Std. dev. of employee age</td>
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<td>0.141</td>
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<td>(0.067)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.068)</td>
<td>(0.069)</td>
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<td>Horizontal pay dispersion</td>
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<td>(0.006)</td>
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<tr>
<td>Vertical pay differential</td>
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<td>0.0590</td>
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<td></td>
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<td>(0.031)</td>
<td>(0.035)</td>
<td>(0.035)</td>
<td></td>
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<tr>
<td>Vertical tournament incentives</td>
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<td>(0.005)</td>
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<tr>
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<td>0.640</td>
<td>0.640</td>
<td>0.652</td>
<td>0.652</td>
<td>0.634</td>
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<td>236.0</td>
<td>234.7</td>
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<td>19</td>
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<td>22</td>
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</tbody>
</table>

Notes: (1) This table reports fractional logit regression estimation on the fraction of a firm’s patent citations towards exploratory content; (2) Number of observations = 381; (3) Number of firms = 81; (4) 2-digit SIC industry dummies included in all models; (5) Calendar year dummies included in all models; (6) Standard errors in parentheses; (7) Average employee age scaled (divided by 10); (8). * p < 0.05. + p < 0.1.

### Table 6b
Fractional logit regressions on proportion of exploratory patents.

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Constant</td>
<td>−2.051</td>
<td>−2.018</td>
<td>−2.072</td>
<td>−2.180</td>
<td>−2.128</td>
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<td>(0.784)</td>
<td>(0.785)</td>
<td>(0.784)</td>
<td>(0.791)</td>
<td>(0.792)</td>
<td>(1.028)</td>
<td></td>
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<td>Firm size</td>
<td>−0.065</td>
<td>−0.068</td>
<td>−0.067</td>
<td>−0.068</td>
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<td>(0.034)</td>
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<td>(0.035)</td>
<td>(0.035)</td>
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<tr>
<td>(0.365)</td>
<td>(0.366)</td>
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<td>Financial slack</td>
<td>0.126</td>
<td>0.131</td>
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<td>0.132</td>
<td>0.125</td>
<td>0.133</td>
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<td>(0.046)</td>
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<td>(0.047)</td>
<td></td>
</tr>
<tr>
<td>Past 5-yr exploratory patent ratio (lagged by 1yr)</td>
<td>3.971</td>
<td>3.965</td>
<td>4.024</td>
<td>3.975</td>
<td>4.025</td>
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</tr>
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<td>(0.211)</td>
<td>(0.211)</td>
<td>(0.214)</td>
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<td>(0.215)</td>
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<tr>
<td>Pay level</td>
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<td>0.513</td>
<td>0.166</td>
<td>0.360</td>
<td>0.435</td>
<td>0.535</td>
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<tr>
<td>(0.174)</td>
<td>(0.221)</td>
<td>(0.203)</td>
<td>(0.175)</td>
<td>(0.236)</td>
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<tr>
<td>Average employee age</td>
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<td>(0.206)</td>
<td>(0.205)</td>
<td>(0.206)</td>
<td>(0.207)</td>
<td>(0.209)</td>
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<td>(0.099)</td>
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<td>× Std. dev. of employee age</td>
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<td>21</td>
<td>22</td>
</tr>
</tbody>
</table>

Notes: (1) This table reports fractional logit regression estimation on the fraction of a firm’s patents that are exploratory; (2) Number of observations = 381; (3) Number of firms = 81; (4) 2-digit SIC industry dummies included in all models; (5) Calendar year dummies included in all models; (6) Standard errors in parentheses; (7) Average employee age scaled (divided by 10); (8). ** p < 0.01. * p < 0.05. + p < 0.1.
Table 6c  
Fractional logit regressions on originality.

<table>
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<tbody>
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<td>Constant</td>
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<td>−0.428</td>
<td>−0.522</td>
<td>−0.691</td>
<td>−0.613</td>
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<td>Firm size</td>
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<td>0.006</td>
<td>0.005</td>
<td>0.001</td>
<td>0.002</td>
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<tr>
<td>R&amp;D intensity</td>
<td>1.034</td>
<td>0.985</td>
<td>1.031</td>
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<td>0.956</td>
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<td>0.005</td>
<td>0.002</td>
<td>0.008</td>
<td>0.014</td>
<td>0.018</td>
</tr>
<tr>
<td>Past 5-yr exploratory patent ratio (lagged by 1 yr)</td>
<td>1.350</td>
<td>1.327</td>
<td>1.348</td>
<td>1.352</td>
<td>1.319</td>
<td>1.329</td>
</tr>
<tr>
<td>Pay level</td>
<td>−0.310</td>
<td>−0.034</td>
<td>−0.306</td>
<td>−0.287</td>
<td>0.042</td>
<td>0.091</td>
</tr>
<tr>
<td>Average employee age</td>
<td>0.542</td>
<td>0.512</td>
<td>0.542</td>
<td>0.531</td>
<td>0.498</td>
<td>0.427</td>
</tr>
<tr>
<td>Std. dev. of employee age</td>
<td>−0.287</td>
<td>−0.275</td>
<td>−0.267</td>
<td>−0.273</td>
<td>−0.259</td>
<td>−0.420</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>−0.011</td>
<td>−0.011</td>
<td>−0.012</td>
<td>−0.012</td>
<td>−0.082</td>
<td></td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td>−0.001</td>
<td>−0.006</td>
<td>−0.006</td>
<td>−0.006</td>
<td>−0.002</td>
<td></td>
</tr>
<tr>
<td>Vertical tournament incentives</td>
<td>0.276</td>
<td>0.326</td>
<td>0.326</td>
<td>0.322</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Horizontal pay dispersion × Std. dev. of employee age</td>
<td>0.700</td>
<td>0.703</td>
<td>0.702</td>
<td>0.703</td>
<td>0.708</td>
<td>0.712</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.700</td>
<td>0.703</td>
<td>0.702</td>
<td>0.703</td>
<td>0.708</td>
<td>0.712</td>
</tr>
<tr>
<td>Dev</td>
<td>254.1</td>
<td>254.4</td>
<td>254.1</td>
<td>254.5</td>
<td>255.0</td>
<td>255.7</td>
</tr>
<tr>
<td>Df</td>
<td>18</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td>21</td>
<td>22</td>
</tr>
</tbody>
</table>

Notes: (1) This table reports fractional logit regression estimation on average originality of the firm’s patents in a given year; (2) Number of observations = 381; (3) Number of firms = 81; (4) 2-digit SIC industry dummies included in all models; (5) Calendar year dummies included in all models; (6) Standard errors in parentheses; (7) Average employee age scaled (divided by 10); (8).  
** p < 0.01.  
* p < 0.05.  
+ p < 0.1.

Table 6d  
Fractional logit regressions on technology proximity.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.565</td>
<td>0.641</td>
<td>0.572</td>
<td>0.575</td>
<td>0.702</td>
<td>−1.015</td>
</tr>
<tr>
<td>Firm size</td>
<td>0.296</td>
<td>0.296</td>
<td>0.295</td>
<td>0.296</td>
<td>0.294</td>
<td>0.294</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.782</td>
<td>0.776</td>
<td>0.795</td>
<td>0.782</td>
<td>0.804</td>
<td>0.826</td>
</tr>
<tr>
<td>Financial slack</td>
<td>−0.043</td>
<td>−0.039</td>
<td>−0.047</td>
<td>−0.044</td>
<td>−0.048</td>
<td>−0.054</td>
</tr>
<tr>
<td>Past 5-yr exploratory patent ratio (lagged by 1 yr)</td>
<td>−1.391</td>
<td>−1.405</td>
<td>−1.373</td>
<td>−1.389</td>
<td>−1.364</td>
<td>−1.404</td>
</tr>
<tr>
<td>Pay level</td>
<td>0.165</td>
<td>0.298</td>
<td>0.088</td>
<td>0.163</td>
<td>0.167</td>
<td>0.144</td>
</tr>
<tr>
<td>Average employee age</td>
<td>0.311</td>
<td>0.288</td>
<td>0.269</td>
<td>0.311</td>
<td>0.290</td>
<td>0.290</td>
</tr>
<tr>
<td>Std. dev. of employee age</td>
<td>−0.0410</td>
<td>−0.026</td>
<td>−0.039</td>
<td>−0.042</td>
<td>−0.018</td>
<td>0.175</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>−0.006</td>
<td>−0.007</td>
<td></td>
<td></td>
<td>0.083</td>
<td></td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.083</td>
</tr>
<tr>
<td>Vertical tournament incentives</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td>Horizontal pay dispersion × Std. dev. of employee age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.018</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.026</td>
<td>0.996</td>
<td>1.031</td>
<td>1.030</td>
<td>0.999</td>
<td>1.008</td>
</tr>
<tr>
<td>Dev</td>
<td>372.5</td>
<td>360.6</td>
<td>373.4</td>
<td>373.0</td>
<td>359.7</td>
<td>361.8</td>
</tr>
<tr>
<td>Df</td>
<td>18</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td>21</td>
<td>22</td>
</tr>
</tbody>
</table>

Notes: (1) This table reports fractional logit regression estimation on the technology proximity of a firm’s patents in a given year to those in previous five years; (2) Number of observations = 381; (3) Number of firms = 81; (4) 2-digit SIC industry dummies included in all models; (5) Calendar year dummies included in all models; (6) Standard errors in parentheses; (7) Average employee age scaled (divided by 10); (8).  
** p < 0.01.  
* p < 0.05.  
+ p < 0.1.
hierarchy. This variable is indicative of the degree of the promotion tournament in the firm. All else controlled for, tournament incentives in a firm’s vertical compensation design appears to be significantly and positively related to the proportion of exploratory citations in the firm. A standard deviation increase in the vertical tournament incentives of the firm is associated with an increase in the proportion of exploratory citations in the firm’s patents by 10 percent (exp[0.287*0.333]).

The measures for horizontal and vertical pay structure are entered into model 5 together. When the vertical pay differential is accounted for, vertical tournament incentives remains statistically significant at p < 0.1 level, while vertical pay differential becomes not significant. This suggests to us that in the design of vertical compensation structure, the rate at which compensations increase along promotions (the shape of the promotion-pay-increase curve) matters more than the top-to-bottom gap in the compensation hierarchy.

In Table 6b, we replicate the estimations in Table 6a for our second exploratory innovation indicator—proportion of exploratory patents. The results are largely consistent in pattern with those from Table 6a. Between the two vertical structure measures, we don’t observe any relationship between vertical pay differential and proportion of exploratory patents. However, there is still a marginally significant relationship between a firm’s vertical tournament incentives and the proportion of exploratory patents. A standard deviation increase in the vertical tournament incentives of the firm is associated with an increase in the proportion of exploratory patents by 7.1 percent (exp[0.287*0.241]).

In Table 6c, we run estimations on our third exploratory innovation indicator—average originality of the patents filed by a firm in a given year. The result regarding the relationship between vertical tournament incentives and exploration is largely consistent with those observed in our estimations on proportion of exploratory citations (Table 6a) and proportion of exploration patents (Table 6b). Based on model 4, a standard deviation increase in the vertical tournament incentives of the firm is associated with an increase in the average originality in the firm’s patents by 8.2 percent (exp[0.287*0.276]). There also exists a marginally significant negative correlation between horizontal pay dispersion and average originality of a firm’s patents. This result alone is certainly not sufficient for us to come to the conclusion that our hypothesis 1 is supported. Nonetheless, it offers more reason for us to further explore whether the relationship between horizontal dispersion and exploration exists under some of the conditions, which we describe in the next section.

Lastly, we run fractional logit estimations on our fourth exploration indicator—technology proximity in Table 6d. Models 2–5 in Table 6d report the core results regarding the relationships between horizontal and vertical structural measures and technology proximity. There is no statistically significant relationship between any of the horizontal and vertical structural measures and technology proximity.

Recall that our first three dependent variables, estimated in Tables 6a–6c, focus more on the novel knowledge recombination aspect of exploration and our fourth dependent variable, estimated in Table 6d, focuses more on the shifts in technology portfolio across technological (patent-class) boundaries. Across our Tables 6a–6c, the regressions suggest a relationship between vertical tournament incentives and exploration, though the level of statistical significance of this relationship is generally at p < 0.1 level, most likely due to the small sample size. Nonetheless, this relationship shows up consistently across regressions on all of the three exploration indicators in Tables 6a–6c. In Table 6d, however, we find no statistically significant evidence regarding the relationship between vertical tournament incentives and exploration as measured by technology proximity. Taking stock of all four sets of estimations, we find that the general pattern is consistent across measures: the link between vertical tournament structure and exploration is stronger with regard to how exploratory innovations are built upon novel combination of knowledge than to shifts of innovation portfolio across technology classes. This suggests that within the technology classes that a firm specializes in, tournament incentives in vertical pay structure are significantly related to R&D employees’ path-breaking innovations.

5.1. Scope condition for horizontal pay dispersion

In our main estimations, we find a negative relationship (with marginally statistical significance) in Table 6c between horizontal pay dispersion and average originality of the patents filed by a firm in a year. However, in our estimations on the proportion of exploratory citations, proportion of exploratory patents and technology proximity, we do not observe any statistically significant relationship between horizontal pay dispersion and exploration. To adjudicate across these findings, we explore whether there is any scope condition underlying this relationship.

Recall that in proposing the negative relationship between horizontal pay dispersion and exploration, the mechanism we rely on in driving our argument is social comparison. A more varied pay structure (with a higher level of horizontal pay dispersion) seems to elicit a stronger sense of social comparison, which in turn, may dampen the collaboration needed for exploratory innovation.

If social comparison is really at work in linking horizontal pay dispersion to exploration, then based on previous research (e.g., Tsui et al., 1992; Zenger and Lawrence, 1989), we shall anticipate that the occurrence of social comparison is not uniform across various types of demographic groups or situations. For example, Festinger’s (1954) much-cited finding show that social comparison happens more often between people who are similar to each other. This suggests to us that the extent of social comparison shall be greater in firms hiring employee with similar profiles (less diversity) than in firms where employee profiles are more diverse.

In our setting, we use a demographic variable, age, as a proxy for gauging similarity in employee profile. Individuals who are similar in age are likely to have similar level of skills and also pursuing similar goals as each other. As such, in R&D groups where employee age variation is small, we anticipate social comparison will be more intense. Prior research also suggests that comparison of compensation between people similar to each other would evoke a stronger feeling of inequitable treatment (Baron and Pfeffer, 1994; Bloom, 1999; Lazear, 1989; Shaw et al., 2002). This implies that if social comparison does take place among the R&D workforce of a firm, the negative feeling invoked from the comparison may be weaker in firms where employee age variation is larger than in firms with employees of a smaller range of age distribution.

We test this idea by assessing whether the link between horizontal pay dispersion and exploration varies across firms with different level of employee age variance in model 6 of Tables 6a–6d. The results reported for all four measures of exploration support our conjecture that the relationship hypothesized in H1 may be observed only in specific types of employee age distribution. Fig. 1 offers the visualization of the interaction effects. Clearly, there is a scope condition to observe a relationship between horizontal pay dispersion and exploration: the hypothesized negative relationship only exists in firms where the age variation of a firm’s R&D employees (within the same job level) is small. For example, in Fig. 1a, which is based on the estimations on proportion of exploratory citations, there is no negative correlation between horizontal pay dispersion and exploration when employee age variance is at mean level of or at one standard deviation above all firms. Only when a firm’s employee age variance is at the smaller end of the distribution do we observe the hypothesized negative correlation. This same pattern shows consistently across all of the four exploration measures in Fig. 1a–d (based on model 6 of Tables 6a–6d). We conclude from these results that the hypothesized negative relationship between horizontal pay dispersion and exploration exists, but only in firms that have employed R&D staff of very similar demographic (in our analyses, age) profiles.
5.2. Robustness checks

Multiple R&D Locations. Since the firms included in our data are mostly large public firms, some might have multiple locations. For example, only 9.5 percent of our firms have only one R&D location, 7.4 percent have two locations, and 83.1 percent have three or more locations. This raises a legitimate concern whether the mechanisms underlying our hypothesized pay dispersion effects remain robust when a firm’s R&D staff spread across multiple locations. Ideally, if we can breakdown a firm’s patents reliably to their different R&D locations, we would link a location’s compensation structure to that location’s patenting activity. However, such a geographical assignment of firms’ patents is unreliable due to variations in firms’ policies regarding whether their patents are all filed from a central headquarter R&D location or from where the actual R&D activity is performed. Therefore, we decide to analyze our data at the level of a firm rather than a subdivision of a firm.

Clearly, to draw any inference this way about a firm with multiple R&D locations rests on the assumption that the firm’s compensation structure is consistent across its multiple R&D locations. Fortunately, our compensation data contain information of the SMSA locations, states, and regions where a firm operate and we can use that information to assess the validity of this assumption. We calculated the Cronbach’s alpha, which measures the intra-firm correlation of pay dispersions across different locations. The Cronbach’s alpha for horizontal pay dispersion is 0.91, and that for vertical pay dispersion is 0.76, both exceeding the usual threshold of 0.70. Therefore, we believe that pay dispersion structures are consistent across multiple R&D locations of a firm, rendering it reliable for us to draw inference from data analysis at an aggregate (firm) level.

Consistency of Compensation Design across Multiple Levels. One might also be concerned with the aggregated nature of our horizontal pay dispersion measure. As discussed above, our argument about horizontal pay dispersion is built on the assumption that employees within a pay band compare with each other’s pay and allocate effort accordingly. However, our measure of horizontal pay dispersion used in the estimations of Table 6 is an average across all eight levels of pay band. As such, there is no guarantee that this measure consistently represents the degree of pay dispersion at each individual level of the firm. To address this concern, we performed a test of intra-firm correlation of horizontal pay dispersion across pay bands. The Cronbach’s alpha for this test is 0.95, indicating that most of the firms in our data are using similar structure of pay dispersion across multiple pay bands.

Managers vs. Non-managers. A related concern regards where innovation decisions are made in a firm. As we have discussed in section II, we argue that contemporary firms are flatter in their organization of innovation effort and therefore allow a stronger role for non-executive managers and employees. In addition, even if C-level executives are the main-decision maker for direction of R&D and allocation of resources, the execution of any research project still falls on mid-to-lower tier managers and employees. As such, a firm’s compensation design may shape micro-level incentives, and in turn, the type of innovations being produced.

Nonetheless, question still remains which levels in our observed data–manager or non-manager–are more strongly related to a firm’s patterns of innovation. To address this question, we re-estimated our models, but with all pay dispersion-related variables measured separately for managers, who are classified in the pay structure of sampled firms as in pay levels 6–8, and for non-managers whose pay falls in levels 1–5. By separately assessing the compensation-related measures for managers and non-managers, we can to some extent reduce the level of aggregation in the horizontal pay dispersion measure and see whether our results are mainly driven by a specific level of individuals in the sampled firms.

We report the results (replcation the last column of the Table 6 series) in Tables 7a for managers and 7b for non-managers. Interestingly, the two dimensions of our pay dispersion measures (horizontal and vertical) appear to be differentially related to exploration outcomes.
Taking stock of the results in Tables 7a and 7b, the correlation between horizontal pay dispersion and exploration appears to be more salient at the non-manager level than at the manager level. In contrast, the correlation between vertical pay dispersion and exploration appears to be more salient at the manager level than at the non-manager level. Such results have practical implications for firms’ compensation design. They suggest that a higher level of compensation for the highest positions in middle management seems important as this helps create the pay spread between the top and bottom levels of the middle managers and may incentivize more risk taking and exploration among the managers (in pay levels 6–8 in our data) who have more discretion for the direction of R&D projects and also stand to gain more in compensation should they choose to respond to the tournament incentives.

Alternative Controls. We run robustness tests of our models with inclusion of additional control variables. First, we replicate models in Table 6 series with current year patent application count included as an additional control. Recall our theoretical interest is in the balance of a firm’s innovation—whether it tilts more towards exploration or exploitation, and consequentially our first two exploration measures are constructed as proportion of patents and citations that are exploratory out of total patents and citations. Nonetheless, a firm’s level of innovation, as reflected in the number of patents filed by the firm may be related to the pattern of the firm’s innovation in intricate ways. To tease

### Table 7a
Robustness tests - replication of model 6 of table 6a-d using manager-level measurements.

<table>
<thead>
<tr>
<th></th>
<th>Proportion of Exploratory Citations</th>
<th>Proportion of Exploratory Patents</th>
<th>Originality</th>
<th>Technology Proximity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. dev. of age</td>
<td>0.045</td>
<td>−0.036</td>
<td>−0.072</td>
<td>−0.087</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>0.006</td>
<td>−0.044</td>
<td>−0.014</td>
<td>−0.016</td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td>0.292</td>
<td>0.256</td>
<td>−0.147</td>
<td>0.239</td>
</tr>
<tr>
<td>Vertical tournament incentives</td>
<td>0.012</td>
<td>−0.030</td>
<td>0.010</td>
<td>−0.044</td>
</tr>
<tr>
<td>Horizontal pay dispersion × Std. dev. of age</td>
<td>−0.001</td>
<td>0.005</td>
<td>0.000</td>
<td>0.001</td>
</tr>
</tbody>
</table>

### Table 7b
Robustness tests - replication of model 6 of table 6a-d using non-manager-level measurements.

<table>
<thead>
<tr>
<th></th>
<th>Proportion of Exploratory Citations</th>
<th>Proportion of Exploratory Patents</th>
<th>Originality</th>
<th>Technology Proximity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. dev. of age</td>
<td>0.047</td>
<td>−0.059</td>
<td>−0.323</td>
<td>0.014</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>−0.036</td>
<td>−0.046</td>
<td>−0.040</td>
<td>0.013</td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td>0.023</td>
<td>0.028</td>
<td>−0.107</td>
<td>−0.004</td>
</tr>
<tr>
<td>Vertical tournament incentives</td>
<td>−0.000</td>
<td>0.014</td>
<td>0.145</td>
<td>0.001</td>
</tr>
<tr>
<td>Horizontal pay dispersion × Std. dev. of age</td>
<td>0.006</td>
<td>0.006</td>
<td>0.005</td>
<td>−0.001</td>
</tr>
</tbody>
</table>

### Table 8
Robustness tests - regressions controlling for current year patent count.

<table>
<thead>
<tr>
<th></th>
<th>Proportion of Exploratory Citations</th>
<th>Proportion of Exploratory Patents</th>
<th>Originality</th>
<th>Technology Proximity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current year patent count</td>
<td>0.008</td>
<td>−0.001</td>
<td>0.009</td>
<td>0.157</td>
</tr>
<tr>
<td>Std. dev. of age</td>
<td>−0.042</td>
<td>−0.238</td>
<td>−0.049</td>
<td>0.081</td>
</tr>
<tr>
<td>Horizontal pay dispersion</td>
<td>0.006</td>
<td>0.034**</td>
<td>−0.080</td>
<td>0.040</td>
</tr>
<tr>
<td>Vertical pay differential</td>
<td>0.046</td>
<td>0.034*</td>
<td>0.003</td>
<td>0.033</td>
</tr>
<tr>
<td>Vertical tournament incentives</td>
<td>(0.035)</td>
<td>0.033*</td>
<td>(0.037)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Horizontal pay dispersion × Std. dev. of age</td>
<td>(0.015)</td>
<td>(0.161)+</td>
<td>(0.169)+</td>
<td>(0.260)</td>
</tr>
</tbody>
</table>

Notes: (1) Managers are on pay levels 6-8 and non-managers are on pay levels 1-5 in our sample. (2) Number of observations = 381; Number of firms = 81; (3) All models include the standard set of controls used in Table 6; (4) Standard errors in parentheses; (5)** p < 0.01, * p < 0.05, + p < 0.1.

for managers and non-managers. Taking stock of the results in Tables 7a and 7b, the correlation between horizontal pay dispersion and exploration appears to be more salient at the non-manager level than at the manager level. In contrast, the correlation between vertical pay dispersion and exploration appears to be more salient at the manager level than at the non-manager level. Such results have practical implications for firms’ compensation design. They suggest that a higher level of compensation for the highest positions in middle management seems important as this helps create the pay spread between the top and bottom levels of the middle managers and may incentivize more risk taking and exploration among the managers (in pay levels 6–8 in our data) who have more discretion for the direction of R&D projects and also stand to gain more in compensation should they choose to respond to the tournament incentives.

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apart the influence of current year innovation level, we re-run Tables
6a–6d with current year innovation count as an additional control and
report our results in Table 8. We draw two main conclusions from this
set of robustness tests. First, with the exception of technology proxim-
ity, it seems that current year patent count itself is not related to the
proportions of firms’ exploratory citations and patents, or their average
originality of patent innovations. This suggests to us that there is no
strong link between the quantity (level) of innovations produced by a
firm and its exploration in terms of novel combination of knowledge.
Second, after holding constant a firm’s current year patent application
count, evidence largely persists with regard to the relationships be-
tween the way a firm organizes its horizontal and vertical pay structure and
the pattern of its innovations. We therefore conclude that our
findings reported in the main estimations (Table 6 series) are robust to
the inclusion of measure of current level of innovation.

Second, we replicate Table 6 series with an additional control
variable of Past 5-yr patent count. We add this variable to account for
the extent that a firm’s current year pattern of innovation regarding
exploration and exploitation is dependent upon its stock of innovations.
For example, in constructing our first two measures of exploration—
proportion of exploratory citations and proportion of exploratory patents—we
compare a firm’s current year patent innovations against the stock of
patents generated by the firm in the previous five years. As such, the
more a firm has accumulated a rich stock of patent innovations in the
past, the more difficult it is for the firm to break away from old paths.
The inclusion of this additional variable is to make sure that in assessing
the relationship between the measures of pay structure and exploration
outcomes, our estimators have held constant the level of past patent
innovations of the firm. The results are available from the authors upon
request and they remain largely consistent with those from our main
estimations reported in Table 6 series.

6. Conclusion and Discussion

Our paper investigates the relationship between firms’ compensa-
tion structure and the pattern of their innovations as reflected in their
patented knowledge. Specifically, we examine how horizontal pay
dispersion and tournament incentives in vertical pay structure are re-
lated to a firm’s exploration versus exploitation. Building on the pre-
mises that exploratory innovation is characterized by high uncertainty
and risk, as well as dependence on effective employee collaboration, we
hypothesize that horizontal pay dispersion has a negative relationship
with exploration and tournament incentives in vertical pay structure
may either promote or demote exploration.

To test the hypotheses, we link HR compensation records of 81 U.S.
technology firms to patent data of these firms. The HR compensation
data allow us to construct measures for firms’ compensation structure,
and using the patent data we have constructed four different indicators
of a firm’s exploration activities. Our estimations yield two major
findings. First, there is evidence suggesting that tournament incentives
in vertical pay structure is positively associated with a firm’s explora-
tion; this relationship is stronger for exploration indicators that track
the novelty of knowledge elements cited in patents than for the ex-
ploration indicator that tracks changes in the firm’s (patent-class-based)
innovation portfolio. This suggests to us that even though tournament
incentives for R&D employee may not shape the technology portfolio of
the firm, within each technology area, tournament incentives seem to
be related to exploration as revealed by the use of distant knowledge
elements or novel knowledge combination in the generation of in-
novations. Second, across all four exploration indicators, we consis-
tently observe a negative relationship between the horizontal pay
dispersion and exploration in firms where employee age variance is
small. This negative relationship is muted, however, in firms where
employee age variance is large.

Given the above finding, the question remains why firms allow a
compensation system to exist that undermines exploration. We think
this may be due to the fact that a firm’s compensation system is part of
its fundamental corporate infrastructure. It will be rare for any firm to
design its compensation system with only one aspect of consideration
such as exploratory innovation. More likely, a compensation design is
borne out of weighing and balancing multiple factors—legal require-
ment, condition of the labor market, competitor practice, corporate
history and culture, etc. What our research hopes to reveal is that no
matter what the starting point is for a firm to adopt a certain com-
penation design, it has implications for the pattern of the firm’s in-
novations.

Our study contributes by filling in a gap in innovation re-
search—that we lack theoretical explanation and empirical evidence
regarding how a firm’s compensation practices may bear a link to its
exploratory or exploitation-oriented innovation. Scholars have rec-
ognized that employees play a key role in organizational effort to
generate innovation (Subramaniam and Youndt, 2005), and a few stu-
dies have explored the relationship between compensation design and
innovation (Ederer and Manso, 2013; Onishi, 2013; Yanadori and Cui,
2013). Yet, these studies either rely on lab-experimental findings, or do
not specifically consider underlying mechanisms that drive exploration
and exploitation, which is the central question of our paper. We offer
rare empirical evidence that establishes the relationship between an
important aspect of compensation design (horizontal and vertical pay
dispersion) and the extent of exploratory innovation in a firm.

Equally important is that employee age profiles moderate the rela-
tionship between horizontal pay dispersion and the extent of ex-
ploratory innovation. Although certain aspects of workforce diversity
are known to promote innovation (Bell et al., 2011), the interactive
effect of age diversity and compensation design has not been re-
ognized. Our finding that age diversity (i.e., variance of age) mitigates
the negative relationship between horizontal pay dispersion and ex-
ploration offers a new insight into the implication of workforce diver-
sity for innovation. The moderating effect of employees’ age profiles
also contributes to the debate for the performance effect of horizontal
pay dispersion. Given the conflicting evidence of the effect of pay dis-
ispersion on organizational performance, researchers have recently
started to consider the role of work and organizational contexts (Conroy
et al., 2014). Our study joins this burgeoning stream of literature that
identifies the moderating effect of workforce characteristics. While we
focus on employee age profiles, other profiles (e.g., gender composition,
human capital level) might also serve as a context that is relevant to pay
dispersion, which could be investigated in future research.

While we provide the first, as far as our knowledge is concerned,
empirical assessment of the relationship between a firm’s non-execu-
tive-level compensation structure and its exploratory innovation out-
come, we recognize several weak aspects in our assessment. First, while
we have articulated theoretical mechanisms related to the way com-
penration structure affects firm innovation patterns, we are not able, as
we noted in the method section, to empirically establish causality in our
analysis. As such, the risk of reverse causality exists in our research
design. There is also the possibility that some unobserved common
factors drive both changes in exploration and changes in a firm’s com-
ensation structure. Our estimation may be biased due to the
omission of such common third factors.

There are possible alternative interpretations for the results we
obtained in our estimations. For example, we observed in our estima-
tions that there is a correlation between vertical pay dispersion and
exploration. The theoretical explanation we build on is related to the
tournament theory: that when a firm’s vertical compensation design
displays more tournament-structured incentives, employees will likely
take on more risks and pursue explorative research projects. However, a
possible alternative explanation may be that a firm that pursues ex-
plorative projects prefers to disproportionally incentivize middle-to-
higher-level managers. Another possible alternative explanation relates
to firms’ hiring practices — the outcome we observed in our data may
be driven by the types of employees being hired into these firms. These
firms may offer higher compensation to hire high quality middle-to-higher level managers who can effectively manage exploratory projects; consequently, vertical pay dispersion widens. These are all possible contestant interpretations to the one we introduced in our main text. Our empirical setting cannot fully rule out these alternative interpretations.

Second, due to the limitation of the data available, we are limited in our ability to directly measure the social comparison and tournament processes. There are several plausible mechanisms underlying the relationship between pay structure and exploration (e.g., employee networks, trust, cooperation, firms’ ability to evaluate innovation effort or performance). These potential mechanisms are valuable along the explanatory pathway, as they would have greatly enriched our research if we were able to identify them. However, we are not able to empirically tease out various possible nuanced mechanisms that may have contributed to the relationships in question. For these reasons, we interpret our finding as correlational with the hope that future research will find better ways to build on our finding and establish a clean causal pathway empirically.

Third, our theoretical argument is built upon individual motivation for risk-taking and collaborations. As such, the ideal dataset for testing our theory would be one that can allow us to correlate local compensation structure (e.g., of a small R&D unit in one geographical location or at one pay band) with local employee innovation patterns. Unfortunately, we cannot achieve this in our dataset, even though our robustness checks help mitigate the data-aggregation-related concerns to some extent.

In summary, though we urge for caution in interpreting causality in our findings, we have strong confidence that the empirical relationships we have revealed from our investigation are of strong value and relevance to both innovation and HR scholars and practitioners.

Funding

This work was supported by the Social Sciences and Humanities Research Council (SSHRC) of Canada (Grant number: 435-2017-1301, 2017-2022).

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We are indebted to Beth Florin and the late Joseph Rich for making available the data for this study. We are grateful for the feedback from participants of Wharton People and Organization Conference and of the Department of Innovation and Organizational Economics Seminar at the Copenhagen Business School.

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