The Non-linear Relationship between Horizontal Pay Dispersion and Technological Knowledge Production

Lindbjerg, Louise

Publication date:
2023

Document Version
Accepted author manuscript, peer reviewed version

The Non-linear Relationship between Horizontal Pay Dispersion and Technological Knowledge Production

ABSTRACT

Firms' pay structure alter individual and collective behavior through motivation and coordination mechanisms, and thus, designing a pay structure that balances the need to incentivize both individual effort such as hard work and collective effort such as knowledge sharing is a challenge for decision makers trying to incentivize innovation. In this paper, I replicate previous findings that high horizontal pay dispersion among R&D workers, is negatively associated with knowledge production. However, when firm fixed effects are considered the effect becomes positive. I show that this inconsistency is due to a non-linear relationship between pay dispersion measured by the Gini coefficient of R&D employees' salaries and technological knowledge production measured as number of new patent filings. Furthermore, pay dispersion appear only to alter knowledge production in single-establishment settings indicating that social comparison is a driving mechanism, and in settings with a dynamic labor market, i.e., large supply of both R&D employees and R&D intensive firms. These results suggest that the negative externality of pay dispersion kicks in at a later stage and that innovative firms may benefit from a more hierarchical pay structure than what we have thought, traditionally.

Key words: pay dispersion, knowledge production, incentives

Introduction

With roots in the knowledge-based view of the firm (Grant, 1996), it is widely acknowledged that firm innovation to a large extent is determined by the knowledge embedded in organizations' human capital as well as the knowledge sharing among individuals to create new combinations of knowledge (Kogut and Zander, 1992; Tsai, 2001; Grigoriou and Rothaermel, 2014; Haas and Ham, 2015). Consequently, research within the innovation literature looks at firms' human capital, e.g., labor composition and mobility of knowledge workers (e.g., Song, Almeida and Wu, 2003; Singh and Agrawal, 2011; Kaiser et al., 2018) and its effect on invention outcomes. While human capital determines the pool of knowledge available to the firm, organizational structure and practices affects how this pool of knowledge may be utilized through collaboration and motivation mechanisms (Garicano, 2000; Manso, 2011; Patacconi, 2009).

Complementing human capital literature are studies looking at how organizational structure and practices shape decisions and outcomes for R&D and innovation (e.g., Brown and Duguid, 1991; Argyres and Silverman, 2004; Foss, Laursen and Pedersen, 2011). Pay structure is a key organizational practice which is closely linked to organization structure and has been shown to affect multiple organizational outcomes including employee turnover (John Michel, 2002a; Carnahan, Agarwal and Campbell, 2012; Kacperczyk and Balachandran, 2018), firm performance (Brown, Sturman and Simmering, 1996; Bloom and Milkovich, 1998; Bloom, 1999; Lazear, 2000a), and invention (Balkin, Markman and Gomez-Mejia, 2000; Lerner and Wulf, 2007a; Ederer and Manso, 2013; Yanadori and Cui, 2013; Cui, Ding and Yanadori, 2019). Building on social comparison theory and compensation theory, Yanadori and Cui (2013) predict and find a negative relationship between horizontal pay dispersion among R&D employees and patents.

While high pay differentials may be conductive to individual performance through motivation mechanisms, it may be detrimental to collaborative behavior and thereby team performance. High pay differentials may incentivize individuals to prioritize their own performance at the expense of team performance to win the tournament price, i.e., the higher salary (Bloom, 1999; Gerhart & Rynes, 2003). High pay dispersion, especially among employees at the same hierarchical level, that is horizontal pay dispersion, may install feelings of unfairness and distrust due to social comparison which further hinders collaboration (Fredrickson, Davis-Blake and Sanders, 2010). As innovation is a collaborative process relying on knowledge distributed across individuals, the negative consequences of pay dispersion have been argued and shown to outweigh the positive.

Following the method by Kacperczyk & Balachandran (2018), I use International Standard Classification of Occupations (ISCO) to create hierarchical layers within the firm to calculate to horizontal and vertical pay dispersion measured as the Gini coefficient. I rely on data from the European Patent Office (EPO) to measure technological knowledge production. These datasets are linked to the Integrated Database for Labor Market Research (IDA) from Statistics Denmark to obtain individual wages among other information at the individual and firm level. And to identify R&D workers through information on educational background and functional position in the focal firm.

I set out by replicating the finding by Yanadori & Cui (2013) that pay dispersion at the horizontal level, i.e., pay differentials between R&D workers at the same organizational layer is negatively related to new patent filings. Though negative at a first glance, the relationship becomes weekly positive when considering firm-fixed effects. Including a squared term of horizontal pay dispersion, I find a non-linear inverted u-shaped relationship between pay dispersion and knowledge production. Plotting marginal effects reveals that the majority of firms in my sample has pay dispersion below the infliction point at which dispersion becomes detrimental to knowledge production. These results seem to suggest that while the negative effects of pay dispersion on the collaborative nature of knowledge creation holds at a certain level of dispersion, the positive effect of pay inequality appears to outweigh the negative ones at lower levels of dispersion. Hence, by extending the model of Yanadori & Cui (2013), I provide evidence that the optimal structure for innovation may not be as egalitarian as we have traditionally thought (Burns & Stalker, 1994).

I explore the theoretical mechanism of social comparison (Fredrickson et al., 2010) by showing that pay dispersion only seem to impact knowledge production in firms with single R&D establishments as opposed to multiple establishments, indicating that social comparison is a driver when employees can compare themselves and their salaries with colleagues at the same physical location. I also show another interesting boundary condition in that pay dispersion only appear to affect knowledge production when the focal firm is surrounded by a local dynamic labor market with a large presence of R&D intensive firms. Employees may not only compare themselves with co-workers at the same geographical location but also with workers in other firms within the same geographical region. In other terms, social comparison mechanisms seem to span boundaries of the organization.

This paper makes two main contributions to extant literature. First, by providing evidence that past findings of a negative relationship between horizontal pay dispersion and knowledge production may be driven by unobserved time-invariant firm qualities, as the negative effect disappears by the inclusion of firm fixed effects. In firm-fixed models, I show that pay dispersion and knowledge production follows a non-linear u-shaped association. Finding that the relationship between pay dispersion and performance is non-linear has important theoretical and managerial implication when it comes to the mechanisms of pay structure. Second, I identify boundary conditions which suggests that social comparison is the driving mechanisms behind the impact of horizontal pay dispersion on knowledge production. Although preliminary, these results may suggest that the effect of pay structure is not only dependent on internal firm conditions but that the external labor market has to be taken into account by decisions makers designing pay structures in firms.

Theory

Innovation is a complex process relying on the generation of new knowledge and, thus, highly skilled human capital is especially important (Haas & Ham, 2015; Kogut & Zander, 1992). Pay is an important tool in attracting and retaining highly qualified human capital (Andersson et al., 2009; Kacperczyk & Balachandran, 2018). In addition to having an effect on individuals' decision to join or leave the firm, and more importantly for this study, pay also affects individuals' efforts and propensity to collaborate or compete with colleagues while working in the firm (Bloom, 1999). Pay dispersion refers to pay inequality and can be distinguished by a vertical and a horizontal dimension. Vertical pay dispersion refers to wage inequality between organizational layers (Devaro, 2006). A high vertical pay dispersion corresponds to a classic hierarchical organization where pay increases as employee moves up the hierarchical ladders. Horizontal pay dispersion refers to pay inequality within organization layers, hence between employees occupying similar ranks in the firm (Gupta et al., 2012; Siegel & Hambrick, 2005).

Pay Dispersion and Performance

The arguments in favor of high pay dispersion when it comes to performance are tied to individuals' motivation. As such, pay can be viewed in terms of agency theory as a principal-agent problem (Alchian & Demsetz, 1972; Bloom & Milkovich, 1998; Foss & Laursen, 2005). The principal (manager) seeks to maximize agent (employee) effort, while the agent is assumed to minimize effort creating a relationship of divergent interests. By the lack of constant monitoring, setting up a pay structure that incentivizes performance, may provide a solution to the problem of divergent interests, in which agents maximize effort incentivized by maximizing income. Hence, in a setting where individual performance is traceable, a high pay dispersion driven by performance differences should increase performance. Along the same lines, pay is a means to reward employee effort (Gerhart & Rynes, 2003) and can motivate employees to improve their performance (Vroom, 1964). Vertical dispersion, that is consecutively increasing pay by hierarchical layer, may be especially well suited to induce employee motivation and effort as individuals exert more effort in the expectation of future reward (Vroom, 1964), by the expectation of moving up the organization hierarchy to receive higher pay.

High pay variation also increases firms' ability to attract highly qualified human capital such as star scientists as well as retaining the high performers in the firm (Andersson et al., 2009; Kacperczyk & Balachandran, 2018; Lazear, 2000b). However, the sorting argument is less likely to drive performance effects from pay dispersion in my setting as this will increase the pay level of the firm and thereby be controlled out of the analysis both in the construction of the pay dispersion variables and as a control in regression models.

Horizontal pay dispersion, i.e., variation among individuals at the same hierarchical layer, is a means to set up a market-like structure at the workplace where highest performing employees receive larger compensation such that individual effort is rewarded regardless of prospects of moving up the hierarchy (Nickerson & Zenger, 2008). This incentive system may increase competition through social comparison and increase employee efforts (Trevor et al., 2012). But it relies on the ability to measure performance indicators to which the pay is tied. Linking pay to performance motivates employees to increase their performance (Vroom, 1964), but it may have the opposite effect if the pay distribution is perceived as unfair by employees in which case, they may withhold effort (Levine et al., 1993). This is especially true for horizontal dispersion as individuals may perceive pay differential to individuals who are similar to themselves, e.g., at the same rank, as unfair, such that social comparison becomes negative for performance (Fredrickson et al., 2010).

Pay Dispersion and Knowledge Production

Arguments in favor of pay dispersion and performance are tied to individual performance. While individuals' knowledge and entrepreneurial drive play a key role for innovation, creating new knowledge is a collaborative process relying on the shared contributions of multiple individuals (Haas & Ham, 2015; Kogut & Zander, 1992). For this reason, a pay structure that favors collaboration would be the preferred structure for innovation. High pay dispersion may lead individuals to prioritize individual performance over the performance of the team, by for example withholding knowledge to keep a relative advantage over colleagues whom they see as competitors (Pfeffer & Langton, 1993). This is especially detrimental to innovation for which knowledge sharing is an essential component. High pay differentials may evoke feelings of distrust and divide which further hampers collaboration (Levine et al., 1993). These negative effects are expected to be especially present at the horizontal level where they are aggravated by social comparison mechanisms (Fredrickson et al., 2010).

Turning again to agency theory, in addition to being effort-minimizing agents are risk-minimizing (Bloom & Milkovich, 1998; Foss & Laursen, 2005). Innovation activities are inherently risky behavior with a substantial component of exploration of different combinations many of which many fail (Ederer & Manso, 2013). Hence, tying individual pay variation to performance indicators may motivate R&D workers to pursue ideas of lower novelty as these entail less risk (Cui et al., 2019). Uncertainty in innovation outcome also increase errors in performance measures (Holmstrom, 1989; Prendergast, 2002), which is likely to promote feelings of unfairness and dissatisfaction among employees (Gupta et al., 2012; Levine et al., 1993; Pfeffer & Langton, 1993).

These arguments against pay dispersion, especially on the horizontal axis, explains previous negative predictions and findings on pay dispersion and team performance (Bloom, 1999; Yanadori & Cui, 2013). However, most of these arguments are tied to pay dispersion driven by pay for performance. In a call center it is easy to imagine the measurement of performance indicators such as number of phone calls handled, number of customer complaints resolved, or sales numbers. In this setting and other settings where key performance indicators (KPIs) can be traced at a reasonable cost (Lazear, 2000a), pay for performance is expected to be prevalent following the arguments from expectancy theory (Vroom, 1964) and agency theory (Alchian & Demsetz, 1972). However, when it comes to R&D teams and the creation of knowledge, it is much measure performance due to learning and experimentation (Ederer & Manso, 2013). Therefore, I argue, that pay for performance is unlikely to drive pay dispersion among R&D workers.

Instead, pay dispersion among R&D workers may be based in pay differentials linked to a set of observable quality signals at the individual level. R&D workers, namely researchers, differ from the general population of workers in that their relative human capital can be accessed through a number of observables such as the rank of the institution from which they have their degree, patents and awards, and functional specialization. Pay differentials on the basis of these quality indicators may increase effort and motivation by the individuals receiving the pay, because their specific qualities are rewarded (Gerhart & Rynes, 2003). On the other hand, such pay differentials may not have negative effects due to social comparison mechanisms on the motivation of R&D workers receiving a lower compensation, as these pay differentials may be perceived as fair (Levine et al., 1993). Furthermore, researchers may be intrinsically motivated (Amabile, 1997) by the research task itself such that agency-theory predictions on effort-minimization may not be prevalent in the setting of R&D workers.

Assuming that pay dispersion among R&D employees are driven by pay differentials based on individuals' qualities rather than pay for performance, the negative externality of pay dispersion pertains to feelings of divide and inequality which hinders knowledge sharing and collaboration (Pfeffer & Langton, 1993). Such negative effects may only kick in at relatively high levels of pay dispersion such that the positive motivational effects of rewarding individual quality are not outweighed by the negative effects of inequality at lower levels of pay dispersion.

Few empirical studies have been done on the relationship between pay dispersion and knowledge production, most of which consider pay dispersion at the executive level (Amore & Failla, 2020; Balkin et al., 2000; Dechow & Sloan R G, 1991; Holthausen et al., 1995; Lerner & Wulf, 2007). These studies find incentives with a long-time horizon, such as stock options, are beneficial to firm innovation. Executives influence corporate R&D and innovation by directing resources and managerial attention. R&D employees, on the other hand, are at the center of knowledge creation making motivation and collaboration mechanisms driven by pay dispersion more directly linked to innovation. Cui, Ding and Yanadori (2019) show that vertical pay dispersion in the R&D workforce is associated with more exploratory patents while horizontal pay dispersion is negatively associated with exploration. Most closely related to my study, Yanadori and Cui (2013) find a negative correlation between horizontal pay dispersion of R&D workers and number of patents. To the best of my knowledge, my study is the first to theorizing and empirically exploring potential non-linearities.

Following the approach by Yanadori and Cui (2013) I focus on horizontal pay dispersion rather than vertical pay dispersion although I control for the vertical dimension. Vertical pay dispersion, i.e., pay inequality between organizational layers is unlikely to drive performance of R&D teams.

When it comes to R&D employees, their position within the firm hierarchy is relatively stable. If you are a lab technician, you are unlikely to move to a higher layer by a promotion to researcher as these functions require different educational backgrounds. Furthermore, R&D employees when compared to for example business professionals, may prefer to stay in their specialist roles as opposed to climbing the organizational hierarchy to reach supervisor or managerial positions which are of a more general nature. R&D workers are, thus, unlikely to be motivated by tournament incentives.

Data

Empirical Setting

I investigate the relationship between horizontal pay dispersion and knowledge production in the empirical setting of Denmark. This setting is attractive as Danish employers report salaries of employees to a central tax authority implying that individual salaries, and thus, pay structure can be measured accurately. Furthermore, employer-employee linked labor market data allows me to track employees' educational backgrounds as well as functional and hierarchical position in the focal firm providing unique benefits for investigating the relationship between pay dispersion and knowledge production. Datasets used in this paper covers the universe of Danish firms such that a large sample can be obtained even with the sample restriction that firms need to be R&D intensive. A large and balanced panel enables the inclusion of firm fixed effects which are relative demanding on the statistical power of models. As results will demonstration, controlling for time-invariant firm qualities is important in identifying the association between pay and patents.

In Denmark, wages are to a large extent determined by collective bargains between labor unions and employers implying that employees in the same job functions and seniority ranks have similar base salaries. Hence, variation in pay tends to come from bonused based on qualifications and performance. This also implies that dispersion to a large extent is driven by variation in the higher end of the pay distribution as opposed to the lower end. Potential negative effects of increased pay dispersion are, thus, unlikely to arise because of variation in the lower end of the pay distribution where individuals withhold effort due pay below their hygiene wage.

Linked Employer-Employee Data and Patent Data

The Integrated Database for Labor Market Research (IDA) provided by the national statistics bureau, Statistics Denmark, is used to identify individual salaries as well as hierarchical layers inside the firm based on individual occupational codes. I link this dataset to a general firm register to obtain firm-level information including corporation type, firm age, and financial data. A key feature of this dataset is the ability to track linked employer-employee data over time and it has been used in numerous studies published in top journals (for instance, Dahl & Sorenson, 2012; Kaiser et al., 2018; Rocha & van Praag, 2020). Firms can be reliably followed over time from year 1999 and onwards. Patent data from the European Patent Office (EPO) is matched to the IDA data to obtain firm-level measures of new patent applications which I have available until 2012.

Dependent Variables

To measure the relationship between pay dispersion and firms' ability to produce technological knowledge I employ a classic measure of technological knowledge reflected by the *number of new patents* in a given year (Trajtenberg, 1990). Patents are measured as number of patent application filings recorded at the priority date, that is, the first date of filing the application. The advantage of using the priority date as registration of a new patents is that this is the first formal record of new knowledge.

Independent Variables

My main independent variable is horizontal pay dispersion. Following the same approach as Kacperczyk & Balachandran (2018), I use International Standard Classification of Occupations (ISCO) to establish layers within the firm hierarchy and measure pay dispersion within and between theses layers using the Gini Coefficient. This method of constructing the firm hierarchy has been used in multiple studies (Caliendo et al., 2015; Tåg, 2013; Tåg et al., 2016) and creates four layers inside the firm: 1) Management, 2) High knowledge professionals, 3) Medium knowledge professionals, and 4) Basic knowledge professionals. Table 1 illustrates that this approach establishes a classic hierarchy where the number of employees decrease and pay levels increase by rank.

Table 1: **Layers in the firm hiearchy**

Mean	No. of Employees	Pay average (Hourly DKK)
1. Management		
Senior officials and managers	48.583	445.472
2. High knowledge professionals		
E.g. engineers, researchers, business analysts	462.481	269.729
3. Medium knowledge professional		
E.g. technicians, corporate salesmen	386.500	224.833
4. Basic knowledge workers		
E.g. clerks, mashine operators, office secretaries	761.067	182.968

Based on International Standard Classification of Occupations (ISCO)

I restrict my calculation of the Gini coefficient to include only layers; 2) High knowledge professionals and 3) Medium knowledge professionals. Basic knowledge professionals include job functions such as machine operators and cashiers and are assumed not to have any noticeable impact on knowledge creation. The managerial layer is excluded from the Gini coefficient calculation as my theoretical reasoning is built around the relationship between pay differentials among R&D workers and production of knowledge. Incentives at the managerial layer are fundamentally different from those at the worker layers such that theories of future reward and collaboration does not apply to the same extent.

Gini coefficients are calculated for R&D workers within the firm. *R&D workers* are defined as individuals with a higher degree (Bachelor's, Master's, or PhD) in a STEM related field (technical, natural, veterinary, agricultural, and health sciences) occupying high and medium knowledge positions (Kaiser et al., 2015). High knowledge professionals (layer 2) corresponds to researchers, while medium knowledge professionals (layer 3) corresponds to technicians. Individuals' education backgrounds are identified by linking my dataset to a register containing information on highest completed education. Position within the firm hierarchy is determined via International Standards Classification of Occupations codes at the 1-digit level.

Figure 1 illustrates labor composition of the R&D workforce for firms in my sample, while Figure 2 shows the labor composition of all employees having their main occupation with the firm. As one would expect, when considering all employees in the firm, the largest layer is the basic layer while number of employees decease as the rank increases. For R&D employees however, the high knowledge layer is by far the largest indicating the R&D workforce of these R&D intensive firms consist mainly of researchers.

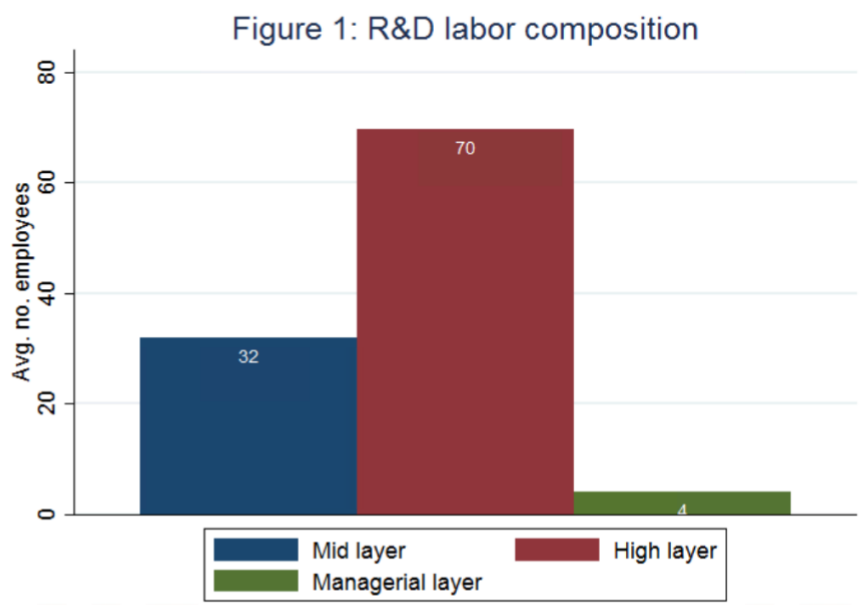


Figure 1: R&D labor composition
Avg. no. employees
0
20
40
60
80
32
70
4
Mid layer
High layer
Managerial layer

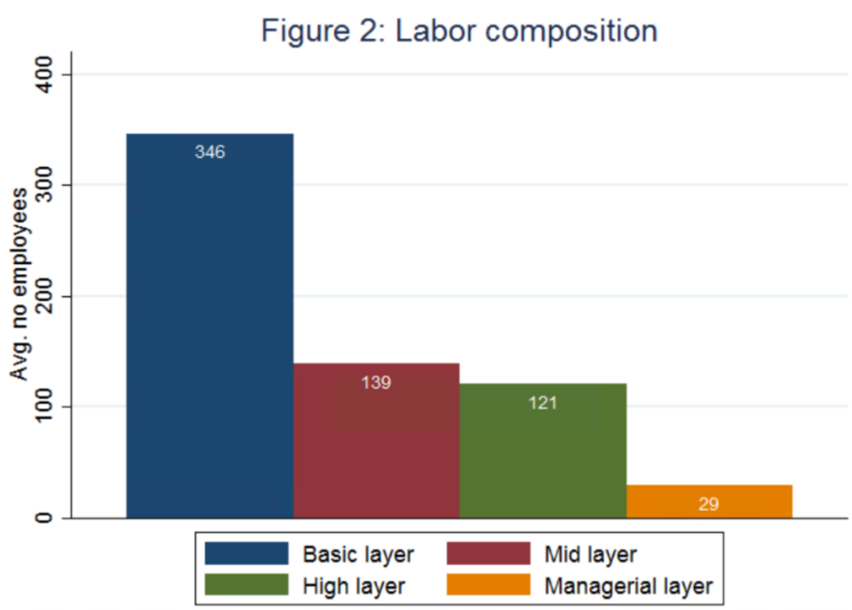


Figure 2: Labor composition
Avg. no employees
0
100
200
300
400
346
139
121
29
Basic layer
Mid layer
High layer
Managerial layer

Following previous research on pay dispersion (e.g., Bloom, 1999; John Michel, 2002b; Sørensen and Sharkey, 2014; Kacperczyk and Balachandran, 2018), I measure pay dispersion by the Gini coefficient which is given by the following formular:

$$Gini = \frac{2\sum_{i=1}^{m} iw_i}{m\sum_{i=1}^{m} w_i} - \frac{m+1}{m} \quad (1)$$

w_i denotes hourly salary of an individual at the *i*th layer in the organizational hierarchy indexed in nondecreasing order and *m* denotes count of workers at a given layer. A Gini coefficient of 0 reflects a situation of total equality where all employees at the layer earns the same while 1 reflects absolute dispersion. After calculating dispersion at each layer, I add them up and divide by the number of layers to obtain the measure of *horizontal pay dispersion.* For the analysis, I include only two layers and restrict my sample to firms with employees in both layers implying that number of layers is always two.

Similar to the approach for the horizontal Gini, the vertical Gini is calculated using average pay within a layer as inputs to formular (1) instead of individual salaries such that w_i equals the average of salaries within a given layer and *m* is the number of layers. Again, the number of layers is always two due to my theoretical focus on R&D workers which are found at two layers within the firm hierarchy. This also means, that the vertical Gini by construction ranges between 0 and 0.5. Using salary averages by group as an input to the Gini coefficient to calculate vertical dispersion is an approach the has been used by several scholars (e.g., Ohtake, 2008; Cowell, 2011; Kacperczyk and Balachandran, 2018) To alleviate concerns of reverse causality, all independent variables including controls are lagged by one year.

Control Variables

I control for a set of factors at the firm-level and worker group-level which may affect patent outcomes. I control for logged *Number of R&D workers* as R&D workers are likely to affect dispersion and patents. A control for *Pay average* is included as horizontal Gini increases with pay level as seen in Figure 4. Furthermore, increased pay levels are likely to increase knowledge production due to the increased ability to attract and retain highly skilled human capital. I control for *average* and *standard deviation* of worker *age* and *tenure* within the firm to capture the level and variation in both tenure on the job market (proxied by worker age) and seniority within in the firm (proxied by tenure) as these are important drivers of pay levels. *Vertical pay dispersion* is included as a control.

I include a host of firm characteristics which may affect firms' ability to produce knowledge. Controls include *firm size* as measured by number of employees (including only those having their main occupation with the firm), *firm age* measured as years since the firm was established, *physical capital* given by the natural logarithm of the book value of firms' fixed assets. The *number of establishments* reflecting the total number of physical working places within the firm is included as a control as physical dispersion of workers may affect both pay dispersion and collaboration mechanisms. I include two dummies controlling for whether the firm is a *publicly traded* company and located in the *capital region* which in this setting is the greater area of Copenhagen. As a measure of investment opportunities and actual investments I control for *sales growth* and the logged value of *net investments*. All models control for year, industry, and firm fixed effects. In robustness checks I include a control for R&D spending as this is an important determinant of innovation potential. This variables comes from the Community Innovation Survey which is a sample as opposed to the full population of firms available in other datasets used for this study. Hence, to preserve a large-unbalanced sample, R&D intensity is not included in main specifications.

Sample

While The Integrated Database for Labor Market Research (IDA) database includes the universe of firms in Denmark (~ 300,000 active firms excl. holding companies but including solo ventures which account for half of the firms) uniquely identified from 1999 and until now, my analysis sample is restricted to the availability of patent data until and including 2012. I restrict my sample to firms with at least six R&D employees at each relevant layer (layer 2 and 3). This leaves me with a sample of 4,151 observations and 838 unique firms for years 2002-2012. I restrict the sample to firms with multiple employees at each firm layer to ensure meaningful variation in the dependent variable. For robustness, different layer size cutoffs are used. This restriction also implies that the sample is representative relatively large and R&D intensive firms compared to the Danish population of firms, but smaller than the average firm size of samples typically used for studies on pay dispersion as these are often American studies for which detailed pay information is only available for a subset of corporations which are typically very large

Descriptive Statistics

Table 2 to shows descriptive statistics for main variables reported for the sampled firms. An average firm in my sample files 1.264 new patent applications per year reflecting the fact that few firms file for new patents regularly. Turning to the measure of horizontal pay dispersion, which is my main explanatory variable, average horizontal Gini coefficient of R&D employees is 0.125 which is slightly lower than comparable variables in related research. Yanadori & Cui (2013) report a horizontal dispersion of 0.177 and Cui et al (2019) report 0.181 for the same variable both in the setting of large American firms. Figure 3 illustrates that horizontal pay dispersion increases with firm size (small < 50, medium <= 250, large > 250 as per OECDs definition) and figure 4 shows that horizontal pay dispersion increases with pay level of the firm such that firms in the upper quartile of the pay distribution have higher pay variation among employees at the same rank as compared to firms at lower quartiles. Interestingly, firms in low-tech industries (OECD definition based on R&D intensity) have higher pay dispersion than firms in medium- and high-tech industries.

Table 2: **Descriptive statistics for main variables**

	Mean	Std. Dev.	Min	Max
Technological knowledge				
Number of patents	1.264	6.659	0	> 130
Pay dispersion	0.125	0.036	0	0.427
Horizontal gini - R&D workers				
Controls: R&D workers				
Vertical gini	0.049	0.035	0	0.254
Number of R&D workers	151.804	428.127	10	> 8,000
Pay average (Hourly DKK)	264.688	46.978	68.5	796.690
Tenure standard deviation	4.748	2.293	0	14.590
Tenure average	4.855	2.589	0	17.389
Age standard deviation	9.340	1.631	2.112	16.032
Age average	41.858	3.919	25.549	57.667
Controls: Firm				
Firm size	1,838.548	6,360.36	16	> 180,000
Firm age	26.039	22.034	0	> 200
Physical capital (thousand DKK)	1,420,076	4,718,249	0	>119,000,000
No. of establishmetns	31.153	82.609	1	> 1,000
Capital region dummy	0.462	0.499	0	1
Public dummy	0.686	0.464	0	1
Investment intensity	0.063	0.132	0	1
Sales growth	16.870	1250.854	-1	> 300

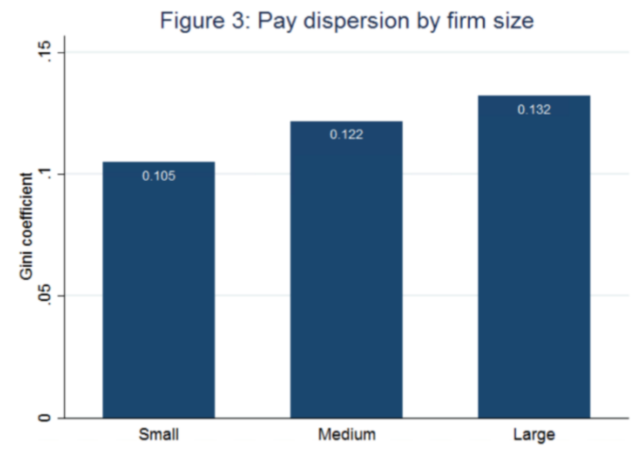


Figure 3: Pay dispersion by firm size
Gini coefficient
0
.05
.1
.15
0.105
0.122
0.132
Small
Medium
Large

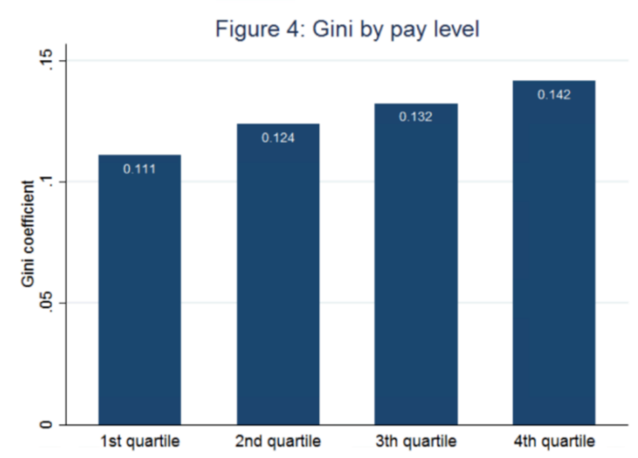


Figure 4: Gini by pay level
Gini coefficient
0
.05
.1
.15
0.111
0.124
0.132
0.142
1st quartile
2nd quartile
3th quartile
4th quartile

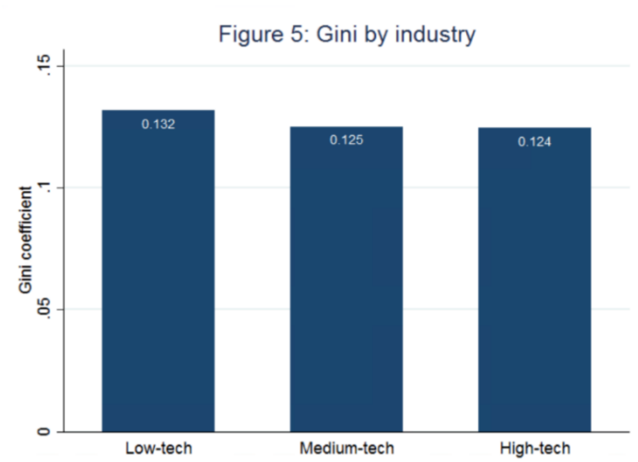


Figure 5: Gini by industry
Gini coefficient
0
.05
.1
.15
0.132
0.125
0.124
Low-tech
Medium-tech
High-tech

The average firm in my sample has 152 R&D workers. R&D workers have, on average, 5 years of experience in the focal firm and an average age of 42. The relative high age may be driven by the high education level of these workers such that they enter le labor market in their thirties. The average firm is 26 years old. 69 percent of firms are publicly traded companies and 46 percent are located in the greater capital region. The average number of establishments within a firm is 31 different physical locations.

Results

I regress patents on a Gini coefficient reflecting horizontal dispersion along with the rich set of control variables. Poisson models which are the natural choice for over dispersed count data with many zeros are used as the dependent variable is patent counts. In addition to Poisson estimations, separate models are estimated by ordinary least squares to allow for the inclusion of firm fixed effects In these model the dependent variable is logged due to its skewed distribution. Given the panel structure of the data and, thus, repeated observations of firms, standard errors are clustered at the firm level in all models. All independent variables are lagged by one year.

Main Results

Table 3 reports the estimated effects of pay dispersion among R&D workers on number of patents as a measure of technological knowledge output or invention. In line with the expectation based on previous research, results in model shows that horizontal pay dispersion is statistically significant and negatively associated with output implying that increased pay inequality among R&D workers appears to be negative for knowledge production. Interestingly, as displayed in model II, the results is positive and significant when the relationship between dispersion and patents is estimated in a linear model with firms fixed effects. Including a squared term of horizontal pay dispersion both the Poisson estimation (model III) and OLS estimation (model IV) shown a non-linear relationship with the original term as positive and the squared term as negative.

Results from table 3 indicates that a certain level of pay differentials among R&D employees is beneficial to reward differences in skills and efforts and that the detrimental effects on collaboration from feelings of inequality and competition only kicks in at higher levels of dispersion.

Table 3: **The effect of horizontal pay dispersion on firms' technological knowledge**

	Model I: Poisson			Model II: OLS			Model III: Poisson			Model IV: OLS		
	Number of patents			Number of patents			Number of patents			Number of patents		
	β	p	s.e.	β	p	s.e.	β	p	s.e.	β	p	s.e.
Pay dispersion												
Horizontal gini	-4.924	0.048	2.491	0.604	0.023	0.266	49.122	0.008	18.553	2.049	0.016	0.847
Horizontal gini squared							-191.632	0.003	64.274	-4.813	0.049	2.439
Controls: R&D workers												
Vertical gini	3.506	0.137	2.356	-0.024	0.948	0.377	4.010	0.088	2.347	0.047	0.900	0.379
Log R&D workers	0.590	0.001	0.174	0.094	0.083	0.054	0.523	0.002	0.171	0.092	0.090	0.054
Pay average	0.005	0.094	0.003	-0.000	0.272	0.000	0.005	0.143	0.003	-0.000	0.345	0.000
Tenure standard deviation	-0.076	0.288	0.071	-0.009	0.433	0.011	-0.063	0.378	0.071	-0.009	0.422	0.011
Tenure average	0.100	0.092	0.059	0.011	0.250	0.009	0.083	0.169	0.060	0.011	0.242	0.009
Age standard deviation	-0.086	0.326	0.087	-0.019	0.016	0.008	-0.092	0.291	0.087	-0.019	0.016	0.008
Age average	-0.205	0.000	0.049	-0.004	0.454	0.006	-0.193	0.000	0.048	-0.004	0.421	0.006
Controls: Firm												
Log Firm size	0.049	0.825	0.221	0.011	0.829	0.050	0.085	0.697	0.218	0.012	0.816	0.050
Log Firm age	0.006	0.225	0.005	-0.016	0.000	0.001	0.006	0.210	0.005	-0.016	0.000	0.001
Log Physical capital	0.627	0.000	0.093	-0.010	0.440	0.013	0.618	0.000	0.093	-0.010	0.451	0.013
No. of establishmetns	-0.018	0.101	0.011	-0.001	0.363	0.000	-0.018	0.081	0.011	-0.001	0.326	0.001
Capital region dummy	0.535	0.018	0.225	0.004	0.957	0.066	0.540	0.017	0.226	0.002	0.972	0.066
Public dummy	0.597	0.108	0.372	0.002	0.975	0.073	0.645	0.089	0.379	0.000	0.997	0.073
Sales growth/investment intensity	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Firm fixed effects	No			Yes			No			Yes		
Number of observations/firms	4,151/838			3,971/660			4,151/838			3,971/660		
Pseudo/Adjusted R^2	0.708			0.846			0.711			0.812		

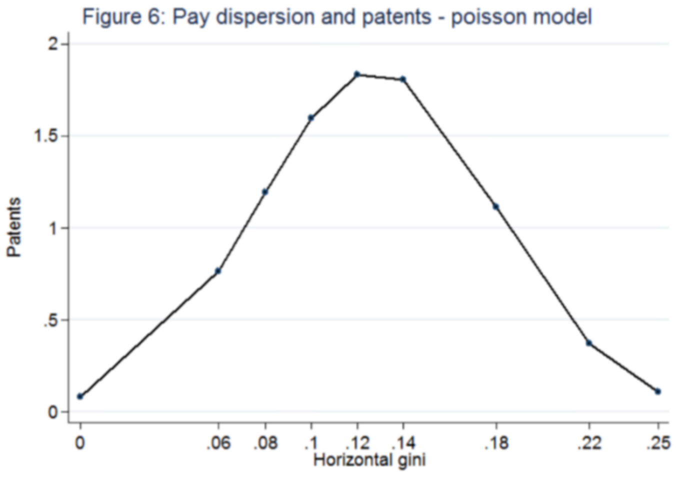
Robust standard errors clustered by firm. Sample restricted to firms with at least 5 R&D employees at relevant firm layers for years 2002-2012. Patents are measured as count of new patent applications (logged in OLS specifications). Model I and model III are poisson estimations and model II and model IV are estimated by ordinary least squares with firm fixed effects. The fixed effects models contain fewer observations as singleton obersvations are dropped.

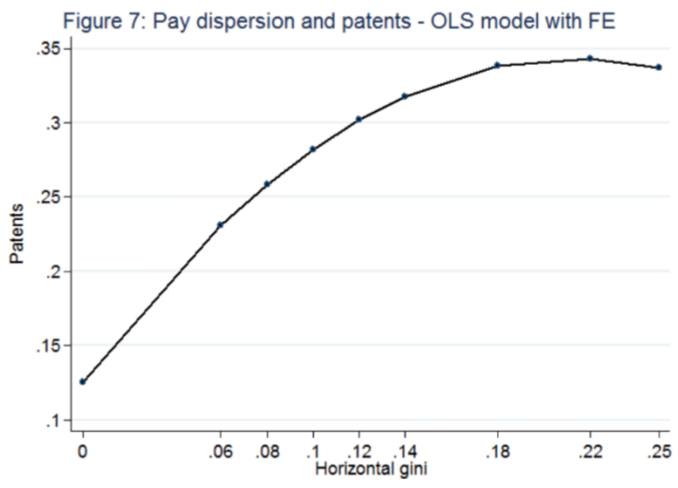
Table 4: **Heterogeneity: Single vs. multi establishment and non-capital vs. capital region**

	Model V: OLS			Model VI: OLS			Model VII: OLS			Model VIII: OLS		
	Number of patents			Number of patents			Number of patents			Number of patents		
Sample	Single-establishment firms			Multi-establishments firms			Non-capital region firms			Capital region firms		
	β	p	s.e.	β	p	s.e.	β	p	s.e.	β	p	s.e.
Pay dispersion												
Horizontal gini	3.728	0.008	1.397	0.189	0.848	0.982	0.772	0.451	1.023	5.021	0.001	1.476
Horizontal gini squared	-9.387	0.019	3.976	0.953	0.745	2.929	-1.855	0.521	2.887	-13.352	0.002	4.318
Controls	Yes			Yes			Yes			Yes		
Sales growth/investment intensity	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Firm fixed effects	Yes			Yes			Yes			Yes		
Number of observations/firms	1,488/283			2,423/410			2,036/354			1,925/309		
Adjusted R^2	0.651			0.870			0.735			0.856		

Robust standard errors clustered by firm. Sample restricted to firms with at least 5 R&D employees at relevant firm layers for years 2002-2012. Patents are measured as count of new patent applications (logged). All models are estimated by ordinary least squares with firm fixed effects. In models V and VI, the sample is split by firms with single and multiple R&D establishments. In models VII and VII, the sample is split by firms located outside capital region and firms located in capital region as a proxy for dynamic labor market.

Plotting the marginal effects of the relationship between horizontal pay dispersion and patents, Figure 6 reveals a clear pattern of increasing and decreasing returns when the relationship is modelled without firm fixed effects. The infliction points at which increased pay dispersion become negative for patent performance is at a Gini coefficient of 0.12 with almost have of firms in my sample having dispersion below this point. These results suggest that many firms may benefit from increasing horizontal pay dispersion as opposed to what previous results without the inclusion of a squared term suggest. In the fixed effects estimation, the negative returns to high pay dispersion is less pronounced and with an infliction point of 0.22 implying that 99 percent of the sample could potentially benefit from increasing dispersion.





Additional Analyses

In table 4, I split the sample by firms with single R&D establishments and firms with multiple R&D establishments. Results from model V and VI shows that pay dispersion only influence knowledge production in settings where all R&D employees are working at the same physical location. This is an interesting boundary conditions which supports the theoretical mechanism of social comparison, by showing that the proposed motivational effect of social comparison only works for co-workers within close proximity. Model VII and VIII shows that pay dispersion matters only for firms located in the capital region which I take as a proxy for dynamic labour market. The capital region has by far the highest concentration of R&D intensive firms and highly skilled individuals. These results suggest that social comparison plays a role beyond firm boundaries as employees compare themselves with workers of similar functions in other firms in close geographical proximity.

Robustness Checks

In this section, I comment on a selection of robustness checks which are displayed in appendix. To alleviate concerns that results are driven by past patent performance, I re-estimate main models controlling for average past three-year patent output. In a separate set of models, I control for R&D intensity which is variable coming from the Community Innovation Survey and is excluded from main models to preserve a large and balanced sample. Table A.2 shows that results are robust to the inclusion of both of these additional controls.

Table A.3 displays the results of re-estimating the main model with different sample cuts with respect to the number of R&D employees at relevant firm layers. Models A-V and A-VI show results of running models with a sample cut of minimum three R&D employees per layer. The signs of main coefficients remains the same but become insignificant in the firm fixed effects model. On the other hand, effect sizes increase when the sample instead is cut at minimum ten

R&D employees at each relevant firm layer as per model A-VII and A-VIII. It is not surprising that pay dispersion matters more in larger team sizes where variation in pay is more likely to occur between members of same function and seniority.

Discussion

In this paper I show, in line with previous studies of pay dispersion and collaborative performance (Bloom, 1999; Yanadori & Cui, 2013), that pay dispersion on the horizontal axis is negatively associated with invention outcomes of firms at least at a first glance. I show, however, that this relationship is non-linear and that increases in horizontal pay dispersion are positively associated with patent output up until a curtain point, after which increases in dispersion becomes negative. Interestingly, most firms would appear to benefit from increases in pay dispersion. These results indicate that the negative effects of increased inequality related to lack of knowledge sharing and feelings of unfairness are outweighed by the positive effects of rewarding differences in employee qualities and efforts.

Horizontal dispersion among R&D employees may not provoke negative feelings as a results of social comparison, because differences in pay can be attributed to measurable quality factors of the individual researcher such as field of specialization, citations, awards, and rank of the institution from which the researcher got her degree. Pay differentials resulting from pay for performance are less likely among R&D employees compared to other business professional as performance in the R&D process is inherently difficult to measure due to a high degree of experimentation (Ederer & Manso, 2013). But if R&D employees are rewarded based on past performance indicators as opposed to current ones, how are they incentivized to increase performance (Alchian & Demsetz, 1972; Vroom, 1964)? Perhaps they are intrinsically motivated by the research itself and pay shall be viewed as a means to incentivize the researcher by rewarding their quality.

Results of the heterogeneity analysis points to important boundary conditions of the influence on pay structure and knowledge production while at the same time finding support of social comparison as a driving mechanic (Fredrickson et al., 2010). Horizontal pay dispersion seem to matter in settings where workers can compare themselves to either co-workers or employees of other firms on close geographical proximity. In sum, this study suggests that increases in pay dispersion may not be detrimental to the creation of knowledge and may even be beneficial in contrast to the idea that knowledge production requires egalitarian structures to promote knowledge sharing (Burns & Stalker, 1994; Yanadori & Cui, 2013).

A key limitation of this study is the lack of ability to draw causal inference. Pay structure may correlate with underlying firm factors such as organizational culture and structure which may affect invention outcomes. An ideal setting to test the effect of pay dispersion on innovation would be a field experiment in which the pay structure of firms is altered to track changes in innovation outputs. A such experiment is infeasible due to costs and ethical issues of altering individuals' pay. Given the observational nature of my data, a source of exogenous variation affecting the pay structure of certain firms or the pay of certain individuals within the firm increase the ability to draw causal inference as such exogenous change in pay would rule out concerns related to the endogenous choice of firm managers to alter pay structure. Though these concerns are to some extent ruled out by the inclusion of a past performance measures and firm fixed effects, richness of the Danish data may enable me and other researchers to get closer at causality in the future.

References

Alchian, A. A., & Demsetz, H. (1972). Production, Information Costs, and Economic Organization. *American Economic Association*, *62*(5), 777–795.

Amabile, T. M. (1997). Motivating Creativity in Organizations: ON DOING WHAT YOU LOVE AND LOVING WHAT You Do. *California Management Review*, *40*(1), 39–58.

Amore, M. D., & Failla, V. (2020). Pay Dispersion and Executive Behaviour: Evidence from Innovation. *British Journal of Management*, *31*(3), 487–504.

Andersson, F., Freedman, M., Haltiwanger, J., Lane, J., & Shaw, K. (2009). REACHING FOR THE STARS: WHO PAYS FOR TALENT IN INNOVATIVE INDUSTRIES?. *The Economic Journal*, *June*, 308–332.

Balkin, D. B., Markman, G. D., & Gomez-Mejia, L. R. (2000). Is CEO Pay in High-Technology Firms Related to Innovation? In *Source: The Academy of Management Journal* (Vol. 43, Issue 6).

Bloom, M. (1999). THE PERFORMANCE EFFECTS OF PAY DISPERSION ON INDIVIDUALS AND ORGANIZATIONS. In ® *Academy of Management Journal* (Vol. 42, Issue 1).

Bloom, M., & Milkovich, G. T. (1998). RELATIONSHIPS AMONG RISK, INCENTIVE PAY, AND ORGANIZATIONAL PERFORMANCE. In ® *Academy of Management Journal* (Vol. 41, Issue 3).

Burns, T., & Stalker, G. M. (1994). *The Management of Innovation*. Oxford University Press.

Caliendo, L., Monte, F., & Rossi-Hansberg, E. (2015). The Anatomy of French Production Hierarchies. *Journal of Political Econemy*, *123*(41), 809–852.

Cowell, F. (2011). *Measuring Inequality*. Oxford University Press.

Cui, V., Ding, W. W., & Yanadori, Y. (2019). Exploration versus exploitation in technology firms: The role of compensation structure for R&D workforce. *Research Policy*, *48*(6), 1534–1549.

Dahl, M. S., & Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management Science*, *58*(6), 1059–1071.

Dechow, P. M., & Sloan R G. (1991). Executive incentives and the horizon problem. *Journal of Accounting and Economics*, *14*, 51–89.

Devaro, J. (2006). Internal promotion competitions in firms. In *RAND Journal of Economics* (Vol. 37, Issue 3).

Ederer, F., & Manso, G. (2013). Is pay for performance detrimental to innovation? *Management Science*, *59*(7), 1496–1513. https://doi.org/10.1287/mnsc.1120.1683

Foss, N. J., & Laursen, K. (2005). Performance pay, delegation and multitasking under uncertainty and innovativeness: An empirical investigation. *Journal of Economic Behavior and Organization*, *58*(2), 246–276.

Fredrickson, J. W., Davis-Blake, A., & Sanders, G. (2010). Sharing the wealth: Social comparisons and pay dispersion in the CEO'S top team. *Strategic Management Journal*, *31*(10), 1031–1053.

Garicano, L. (2000). Hierarchies and the organization of knowledge in production. *Journal of Political Economy*, *108*(5), 874–904.

Gerhart, B., & Rynes, S. (2003). *Compensation: Theory, Evidence, and Strategic Implications*. Wiley.

Gupta, N., Conroy, S. A., & Delery, J. E. (2012). The many faces of pay variation. *Human Resource Management Review, 22*(2), 100–115.

Haas, M. R., & Ham, W. (2015). Microfoundations of knowledge recombination: Peripheral knowledge and breakthrough innovation in teams. *Advances in Strategic Management*, *32*, 47–87.

Holmstrom, B. (1989). AGENCY COSTS AND INNOVATION. In *Journal of Economic Behavior and Organization* (Vol. 2).

Holthausen, R. W., Larcker, D. F., & Sloan, R. G. (1995). Accounting &Economic Business unit innovation and the structure of executive compensation. In *Journal of Accounting and Economics* (Vol. 19). ELSEVIER.

John Michel, B. G. (2002). THE RELATIONSHIPS AMONG ORGANIZATIONAL CONTEXT, PAY DISPERSION, AND MANAGERIAL TURNOVER. *Academy of Management Journal*, *45*(1), 33–42.

Kacperczyk, A., & Balachandran, C. (2018). Vertical and horizontal wage dispersion and mobility outcomes: Evidence from the Swedish microdata. *Organization Science*, *29*(1), 17–38.

Kaiser, U., Kongsted, H. C., Laursen, K., & Ejsing, A. K. (2018). Experience matters: The role of academic scientist mobility for industrial innovation. *Strategic Management Journal*, *39*(7), 1935–1958.

Kaiser, U., Kongsted, H. C., & Rønde, T. (2015). Does the mobility of R&D labor increase innovation? *Journal of Economic Behavior and Organization*, *110*, 91–105.

Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. In *Source: Organization Science* (Vol. 3, Issue 3).

Lazear, E. P. (2000a). Performance Pay and Productivity. *The American Economic Review*, *90*(5), 1346–1361.

Lazear, E. P. (2000b). The Power of Incentives. *American Economic Association, 90*(2), 410–414.

Lerner, J., & Wulf, J. (2007). INNOVATION AND INCENTIVES: EVIDENCE FROM CORPORATE R&D. *The Review of Economics and Statistics*, *89*(4), 634–644.

Levine, D. I., Dickens, J. B. B., Jonathan, L., Lee Levine, J. L., & Janet, Y. (1993). What Do Wages Buy? *Administrative Science Quarterly, 38,* 462–483.

Manso, G. (2011). Motivating Innovation. In *THE JOURNAL OF FINANCE •: Vol. LXVI* (Issue 5).

Nickerson, J. A., & Zenger, T. R. (2008). Envy, comparison costs, and the economic theory of the firm. *Strategic Management Journal*, *29*(13), 1429–1449. https://doi.org/10.1002/smj.718

Ohtake, F. (2008). Inequality in Japan. *Asian Economic Policy Review*, *3*(1), 87–109.

Patacconi, A. (2009). Coordination and Delay in Hierarchies. In *Source: The RAND Journal of Economics* (Vol. 40, Issue 1).

Pfeffer, J., & Langton, N. (1993). The Effect of Wage Dispersion on Satisfaction, Productivity, and Working Collaboratively: Evidence fronn College and University Faculty. *Administrative Science Quartely 38*, *38*, 382–407.

Prendergast, C. (2002). The Tenuous Trade-off between Risk and Incentives. *Journal of Political Economy*, *110*(5), 1071–1102.

Rocha, V., & van Praag, M. (2020). Mind the gap: The role of gender in entrepreneurial career choice and social influence by founders. *Strategic Management Journal*, *41*(5), 841–866.

Siegel, P. A., & Hambrick, D. C. (2005). Pay disparities within top management groups: Evidence of harmful effects on performance of high-technology firms. *Organization Science*, *16*(3), 259–274.

Sørensen, J. B., & Sharkey, A. J. (2014). Entrepreneurship as a Mobility Process. *American Sociological Review*, *79*(2), 328–349. https://doi.org/10.1177/0003122414521810

Tåg, J. (2013). Production hierarchies in Sweden. *Economics Letters*, *121*(2), 210–213.

Tåg, J., Åstebro, T., & Thompson, P. (2016). Hierarchies and entrepreneurship. *European Economic Review*, *89*, 129–147.

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. In *Source: The RAND Journal of Economics* (Vol. 21, Issue 1).

Trevor, C. O., Reilly, G., & Gerhart, B. (2012). RECONSIDERING PAY DISPERSION'S EFFECT ON THE PERFORMANCE OF INTERDEPENDENT WORK: RECONCILING SORTING AND PAY INEQUALITY. In *Source: The Academy of Management Journal* (Vol. 55, Issue 3).

Vroom, V. (1964). *Work and motivation*.

Yanadori, Y., & Cui, V. (2013). Creating incentives for innovation? the relationship between pay dispersion in R&D groups and firm innovation performance. *Strategic Management Journal*, *34*(12),

Appendix Supplementary Material

Table A.1: **Correlation table**

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1)	Number of patents	1.00																							
(2)	Number of forward citations to patents	0.82	1.00																						
(3)	Sales from innovation (thousand DKK)	0.21	0.18	1.00																					
(4)	Horizontal gini - R&D workers	0.04	0.02	0.06	1.00																				
(5)	Vertical gini - R&D workers	0.11	0.09	0.05	0.18	1.00																			
(6)	Horizontal gini - Knowledge workers	0.00	-0.00	0.04	0.71	0.16	1.00																		
(7)	Vertical gini - Knowledge workers	0.11	0.09	0.06	0.18	0.66	0.14	1.00																	
(8)	Number of Knowledge workers	0.27	0.28	0.28	0.20	0.01	0.14	0.05	1.00																
(9)	Pay average (Hourly DKK)	0.03	0.03	0.04	0.34	0.03	0.40	0.04	0.09	1.00															
(10)	Tenure standard deviation	-0.04	-0.07	-0.00	-0.05	0.03	-0.08	0.03	-0.02	-0.09	1.00														
(11)	Tenure average	-0.05	-0.06	-0.02	-0.10	0.04	-0.15	0.05	-0.08	-0.05	0.86	1.00													
(12)	Age standard deviation	-0.05	-0.05	-0.01	0.04	-0.00	-0.04	0.01	0.02	-0.06	0.26	0.17	1.00												
(13)	Age average	-0.08	-0.07	-0.03	-0.08	-0.02	-0.10	0.02	-0.03	0.15	0.34	0.40	0.41	1.00											
(14)	Number of managers	0.05	0.04	0.16	0.09	-0.04	0.08	-0.06	0.29	-0.01	-0.03	-0.07	0.04	-0.02	1.00										
(15)	Gini - managers	0.10	0.05	0.13	0.18	-0.05	0.22	-0.05	0.19	0.07	0.07	0.01	-0.04	0.02	0.09	1.00									
(16)	Firm age	0.08	0.05	0.05	0.05	-0.00	0.07	-0.01	0.06	0.04	0.35	0.27	0.09	0.12	0.05	0.19	1.00								
(17)	Physical capital (thousand DKK)	0.25	0.18	0.24	0.22	0.05	0.23	0.06	0.37	0.03	0.10	0.05	0.01	0.10	0.21	0.43	0.17	1.00							
(18)	R&D spending (thousand DKK)	0.24	0.16	0.16	0.07	0.08	0.01	0.09	0.19	0.01	0.06	0.07	-0.07	-0.05	0.04	0.17	0.09	0.27	1.00						
(19)	No. of establishmetns	-0.01	-0.00	0.09	0.16	-0.04	0.13	-0.05	0.53	-0.03	-0.03	-0.09	0.04	0.01	0.57	0.12	-0.01	0.24	0.00	1.00					
(20)	Public dummy	0.05	0.04	-0.02	0.03	-0.00	0.01	0.03	-0.00	-0.07	-0.05	-0.06	-0.02	-0.07	0.01	0.06	0.05	-0.04	-0.02	0.01	1.00				
(21)	Capital region dummy	0.06	0.06	0.01	0.20	0.01	0.11	0.05	0.18	0.41	-0.12	-0.13	0.03	0.04	0.01	0.09	0.07	0.04	0.03	0.09	-0.05	1.00			
(22)	Manufacturing	0.10	0.07	0.08	-0.07	0.04	-0.11	0.03	-0.11	-0.25	0.25	0.27	-0.06	0.02	-0.05	0.13	0.14	0.20	0.22	-0.14	0.14	-0.34	1.00		
(23)	IT & Communications	-0.06	-0.04	0.01	0.02	-0.11	0.09	-0.16	0.09	0.18	-0.20	-0.18	-0.20	-0.13	-0.01	0.02	-0.10	-0.02	-0.05	0.00	0.01	0.16	-0.28	1.00	
(24)	Technical services	0.01	0.00	-0.06	-0.05	0.10	-0.10	0.17	-0.04	-0.01	-0.08	-0.10	0.12	-0.04	-0.06	-0.27	-0.13	-0.31	-0.01	-0.08	-0.10	0.09	-0.44	-0.16	1.00

All pairwise correlations larger than 0.022 (in absolute terms) are significant at the 5% level

Table A.2: **Control for past knowledge production and R&D expenditures**

	Model A-I: Poisson			Model A-II: OLS			Model A-III: Poisson			Model A-IV: OLS		
	Number of patents			Number of patents			Number of patents			Number of patents		
	β	p	s.e.	β	p	s.e.	β	p	s.e.	β	p	s.e.
Pay dispersion												
Horizontal gini	41.599	0.000	11.816	2.191	0.012	0.866	52.827	0.005	18.663	3.006	0.007	1.107
Horizontal gini squared	-133.072	0.001	41.296	-5.276	0.034	2.479	-205.830	0.002	65.203	-7.704	0.017	3.217
Additional controls												
Past patents 3-yr. avg.	1.149	0.000	0.055	0.206	0.000	0.058						
R&D intensity							-0.012	0.079	0.007	-0.000	0.131	0.002
Controls	Yes			Yes			Yes			Yes		
Sales growth/investment intensity	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Firm fixed effects	No			Yes			No			Yes		
Number of observations/firms	4,007/806			3,846/645			3318/714			3142/		
Pseudo/Adjusted R^2	0.820			0.816			0.704			0.823		

Robust standard errors clustered by firm. Sample restricted to firms with at least 5 R&D employees at relevant firm layers for years 2002-2012. Patents are measured as count of new patent applications (logged in OLS specifications). Model I and model III are poisson estimations and model II and model IV are estimated by ordinary least squares with firm fixed effects. The fixed effects models contain fewer observations as singleton obersvations are dropped.

Table A.3: **Alternative sample cuts: three and ten R&D employees per layer**

	Model A-V: Poisson			Model A-VI: OLS			Model A-VII: Poisson			Model A-VIII: OLS		
	Number of patents			Number of patents			Number of patents			Number of patents		
Sample	Three R&D employees per firm layer			Three R&D employees per firm layer			Ten R&D employees per firm layer			Ten R&D employees per firm layer		
	β	p	s.e.	β	p	s.e.	β	p	s.e.	β	p	s.e.
Pay dispersion												
Horizontal gini	36.937	0.002	11.924	0.403	0.245	0.347	50.322	0.027	22.728	4.194	0.019	1.778
Horizontal gini squared	-145.079	0.001	42.585	-0.960	0.393	1.125	-197.897	0.012	78.541	-8.917	0.082	5.120
Controls	Yes			Yes			Yes			Yes		
Sales growth/investment intensity	Yes			Yes			Yes			Yes		
Industry fixed effects	Yes			Yes			Yes			Yes		
Year fixed effects	Yes			Yes			Yes			Yes		
Firm fixed effects	No			Yes			No			Yes		
Number of observations/firms	7,941/1,758			7,474/1.291			2,408/489			2,307/388		
Pseudo/Adjusted R^2	0.723			0.783			0.702			0.831		

Robust standard errors clustered by firm. Sample restricted to firms with at least 3 R&D employees (models A-V and A-VI) and 10 R&D employees (models A-VII and A-VIII) at relevant firm layers for years 2002-2012. Patents are measured as count of new patent applications (logged in OLS specifications). Model I and model III are poisson estimations and model II and model IV are estimated by ordinary least squares with firm fixed effects. The fixed effects models contain fewer observations as singleton obersvations are dropped.