Master Thesis:

Which Companies Pay for Performance?

A Job Content Approach

Master 'Economics of

Management and Organisations'

Academic Year 2016/2017

Supervisor: Prof. Delfgaauw

Second assessor: Prof. Bijkerk

Jan Biermann
Email: 452916jb@student.eur.nl
Student number: 452916jb

Version: 10/08/17

ERASMUS UNIVERSITEIT ROTTERDAM

Abstract

Why do some companies employ performance pay while others do not? For performance pay to lead to the desired results, it needs to be based on a suitable performance measure. Therefore, only firms which can accurately measure performance will introduce such a payment scheme. The availability of a performance measure, in turn, largely depends on the type of work conducted in the firm. Understanding work as a bundle of tasks allows one to analyze the content of this work. I argue that the intensity in routine and non-routine tasks can serve as a predictor for performance pay. Regression analysis using survey data delivers mixed evidence for this relationship. The intensity in non-routine tasks which are manual-physical appears to be negatively associated with the probability to employ performance pay, as hypothesized. The intensity in other types of routine or non-routine tasks does not show a significant effect.

Table of Contents

1. Introduction

Many organizations constantly aim to become more efficient. One potential channel for improvement is the management of human resources. An increasingly popular human resource policy is performance pay: It intends to provide the employees with the right incentives to become more productive. At the beginning of the century, 40% to 50% of US workers were receiving performance pay and its importance has been increasing during the last three decades (Bloom and Van Reenen 2011[1]). These findings illustrate the relevance of performance pay, but also reveal an interesting heterogeneity in the data: While one half of the workers are covered by performance pay, the other half are not. What are the reasons for this heterogeneity?

The existing empirical research on performance pay mainly focuses on how employees react to performance pay once it is introduced (literature following Lazear 2000[2]). At the same time, we have little empirical evidence on why firms decide for or against performance pay. To explain the abovementioned heterogeneity, the thesis assesses performance pay from a different perspective than previous empirical research and focuses on the behavior of the firm rather than the employee. By empirically analyzing which firms employ performance pay, the thesis sheds light on the factors determining a company's decision to introduce performance pay.

This decision is a delicate one to take, since introducing performance pay doesn't always entail the anticipated results: Some studies have demonstrated huge productivity gains and a positive effect on attracting more productive employees (Lazear 2000). Others have shown that employing performance pay under the wrong circumstances will backfire and cause significant damage (Larkin 2014). These mixed findings illustrate that an optimal contract design is highly relevant not only for academic research but also for decision makers in organizations. Introducing performance pay can result in important competitive advantages, but it can also cause serious harm.

---

[1] The authors summarize evidence from several studies including Lawler and Mohrman (2003), Lemieux et al. (2009) and Kruse et al. (2009).

[2] Subsequent studies include Paarsch and Shearer (2000), Shearer (2004), Courty and Marschke (2004), Bandiera et al. (2007), Larkin (2014), Griffith and Neely (2009).

One decisive factor for the success or failure of performance pay is the performance measure. In order to pay for performance, the firm needs to determine a way to evaluate it. If the payment scheme is based on a poor performance measure, it will not lead to the desired productivity gains. It will more likely result in unintended negative consequences, e.g. the agent neglecting important dimensions of the principal's objective (Holmström and Milgrom 1991; Baker 1992). This process of evaluating performance varies largely depending on the profession which characterizes the firm. But why is the contribution of some professions easier to measure than that of others? One way to answer this question is to analyze the typical activities of a job. In other words: Which tasks determine the everyday work of the employee? Some tasks are easy to quantify, while others are difficult to assess. As a result, a suitable performance measure is available for some occupations, but not for others.

As an example, consider the everyday work of a production worker at a car manufacturing company versus the job of a chef in a good restaurant. The performance of the former can be measured quite easily while the contribution of the latter is difficult to assess. One of the underlying reasons appears to be that the work of the production worker is mostly routine: The job requires lots of repetition and could be captured by programmed instructions. In contrast, the chef's work is mostly non-routine: She must react to the orders and special requests of the customers, the seasonal availability of ingredients and create different meals. The thesis will argue that the intensity in routine or non-routine tasks of an occupation can serve as a predictor for performance pay. To present a nuanced view, the analysis will consider different types of routine and non-routine tasks[3].

The remainder of the thesis is structured as follows: Chapter two discusses related literature and develops the hypothesis. Chapter three presents the data, highlights how this data is processed and introduces the empirical proxies for the theoretical constructs. Chapter four contains the empirical analysis: It discusses the identification strategy, introduces relevant control variables, analyzes the regression results, and presents regression diagnostics. The last chapter is a conclusion.

[3] To do so, the thesis will take into account if tasks are cognitive or physical. Note that in the given example the work of both, the production worker and the chef, is rather physical than cognitive.

This master thesis contributes to the existing literature in three different ways. First and most importantly, the thesis explicitly tests if firms' decisions to employ performance pay are in-line with the mechanisms described by economic theory. By doing so, this work provides empirical evidence on the determinants of the firm's decision to employ performance pay. While existing evidence focuses on the reaction of individual workers on performance pay, the thesis builds on this literature and examines the topic from a different angle by asking if firms recognize the different consequences of performance pay and make their decision in accordance to this. Most closely related in this respect is the work of Pendleton et al. (2009). Similarly to the master thesis, it empirically examines the determinants of performance pay and analyzes the same data set. The major novelty of this thesis is introducing job content measures which capture if routine tasks characterize the work in a company. By doing so, the thesis incorporates characteristics of the job content, while Pendleton et al. (2009) can only relate performance pay to information from a management survey. To the best of my knowledge, this work is the first contribution to follow this approach.

Second, to answer the research question, the thesis develops a unique data set by combining two data sources. The first data source is the 'Workplace Employment Relations Study' ('WERS'). This UK-wide study collects a representative sample of British companies and includes data from interviews with employers, employees, and workers' representatives. It contains information on performance pay and many other management practices. The second data source is the 'Occupational Information Network' ('ONET') which is the main source of occupational information in the US. Its data allows relating quantitative job descriptors to occupations from the WERS. From this data, I create job content measures which capture if a job is routine or non-routine. As has been pointed out, the ONET has great potential to enrich research in different fields (Handel 2016). At the same time, the academic literature which makes use of this opportunity is relatively small (ibidem). In this sense, the thesis contributes to the literature by exploring new ways to analyze the ONET within the scope of empirical research.

Third, to analyze the content of an occupation, the thesis adopts the logic of the so-called 'task approach' which has been developed by Autor et al. (2003). It defines work as a series of tasks which need to be performed to accomplish a certain job. This view makes it possible to analyze occupations by focusing on the content of work rather than on other aspects such as required education or wages. The literature following Autor et al. (2003) applies the task approach to different aspects of labor economics and mainly focuses the role of technological advancement and wage structure. The thesis builds on this literature in two ways. First, it relates to this literature by applying the basic theoretical idea. Second, the methodology of the thesis follows an article from this field of research (Acemoglu and Autor 2011) to operationalize the concept of ‘routine’ and ‘non-routine.’ The thesis contributes to this literature by applying the framework to a novel research question.

2. Related literature and hypotheses development

2.1. Related theoretical literature

The theoretical discussion of performance pay[4] in this thesis is grounded on the classical principal-agent theory. A contribution by Holmström (1979) has popularized the concept, and subsequent work builds on this foundational model. The paper views an organization as the relationship between a principal and the agent. The principal (i.e. the firm) owns resources and hires an agent (i.e. the worker). The agent's work is seen as exerting effort which transforms the principal's resource into output. The principal aims to maximize profits, i.e. the difference between the value of the output and the agent's salary. The worker's objective is to maximize her own utility which is a function of the difference between her income and the costs of exerting effort. As a result, the two interests are misaligned, leading to the so-called agency-dilemma. A key aspect is the issue of observability: Since the agent's actions are not observable (or at least not verifiable and thus not contractible), the payment cannot be based on effort. The salary must be tied to the outcome, which is influenced by the agent's effort as well as a random component. Furthermore, the principal is assumed to be risk neutral (or at least less risk averse than the agent). An optimal compensation scheme can be derived from this framework[5].

Because the agent will not exert any effort if the salary is not linked to the output, a flat-wage contract is never optimal in the simplest model. Subsequent work has further developed the framework, introducing aspects which can make paying a flat-wage optimal (Holmström and Milgrom 1991 being the most prominent contribution). To come to this conclusion, two aspects are particularly important: First, the performance measure must be imperfect (Holmström 1979 implicitly assumes that the measure is complete). The costs of performance pay only occur if the performance measure is imperfect. None of the following issues would arise in a world where the agent's performance could be measured perfectly. Second, the worker must be to some degree internally motivated, resulting in some effort under a flat-wage regime. In this framework, the firm must evaluate costs and benefits of including aspects of performance

[4] This chapter understands 'performance pay' as any type of pay scheme which links some part of the compensation to results of individual or group work. Synonymous expressions include incentive pay, bonus pay, variable pay, piece-rate, and contingent pay.

[5] Most important subsequent work following Holmström (1979) includes Eisenhardt (1989), Holmström and Milgrom (1991), Baker (1992), Holmström and Milgrom (1994).

pay based on a performance measure in the contract compared to a flat wage scheme. Introducing performance pay is associated with certain costs which might outweigh the benefits making the introduction of performance pay unreasonable.

Several theoretical contributions have outlined the role of the performance measure and the different ways in which employing performance pay based on a poor performance measure can hurt the organization. If the measure is imperfectly correlated with the result, the agent will 'game the system' (Baker 1992), i.e. direct her effort to increase the measure without contributing to the actual objective of the principal. Furthermore, a poor performance measure could induce effort on satisfying one dimension of the objective while causing the agent to neglect other aspects. This is the case when the performance measure stresses one dimension of the principal's goals at the expense of other facets. One common example is performance pay based on quantity, which leads to decreased quality (Kerr 1975; Holmström and Milgrom 1991[6]). Lazear's theoretical article (1986) discusses hourly wages and piece rates and concludes that a flat hourly wage is preferable in cases where it is very costly to monitor both quality and quantity (p. 421)[7]. All this research illustrates that if the performance pay cannot be based on an appropriate performance measure, the principal might be better off not introducing any performance pay.

2.2. Related empirical literature on performance pay

Research which specifically addresses the firm's decision to introduce performance pay is rare and lacks seminal studies. A study which analyzes this topic is Pendleton et al. (2009), the contribution which is most closely related to this thesis. It examines data from the same data source (WERS) and considers the pay systems of different workplaces similarly to this thesis. However, there are important differences: First, the thesis introduces job content measures which capture if routine tasks characterize an occupation. By doing so, the thesis incorporates characteristics of the job content, while Pendleton et al. (2009) can only relate performance pay to information from the management survey. Second, Pendleton et al. (2009) choose a broader definition of their dependent variable ('contingent pay'), including for example share ownership schemes. The dependent variable of this thesis ('payment by results') can be seen

[6] Kerr (1975) delivers anecdotal evidence, while Holmström and Milgrom (1991) develop a formalized model.
[7] Another potential drawback of performance pay follows directly from the framework: Performance pay typically imposes risk on the risk-averse agent which is costly for the principal.

as a subcategory of contingent pay. Third, my work focuses on cross-sectional analysis of the most recent data (2011), whereas Pendleton et al. (2009) analyze data from 1984 to 2004, at times specifically focusing on the time dimension.

The following paragraphs present an overview of empirical studies which address the reaction of the workers to performance pay. Despite the thesis examining performance pay from a different perspective, this literature is relevant for the analysis of the thesis. If, for example, workers didn't respond to monetary incentives, there would be no reasons for the firm to consider the effects of performance pay. Since the consequences of performance pay are highly context specific, it is crucial to obtain empirical evidence from a naturally occurring environment rather than from a laboratory setting. Therefore, the papers in this section provide evidence from natural field experiments.

Lazear's seminal paper (2000) considers a manufacturer that switches from paying windshield glass installers an hourly wage to a piece wage. He concludes that productivity per worker increases by 44%. The set-up of the study allows analyzing individual data in a before-and-after design. As a result, the productivity gain can be separated into two parts: Half of it is attributed to the incentive effect, the other half is due to sorting toward more productive workers[8]. Furthermore, since the cooperation introduced the new regime at different times at different branches, the paper can distinguish the effects of the new wage scheme from external shocks, affecting the whole company. Lazear's work illustrates that the positive side of performance pay includes not only the rise of the existing workforce's productivity but also positive effects on the composition of the workforce (also compare Lazear 1986 for a theoretical framework).

Subsequent contributions following Lazear (2000) include a series of studies examining the effect of a piece-rate wage on tree planters: Paarsch and Shearer (1999), Paarsch and Shearer (2000), and Shearer (2004). The field experiment of the latter, most prominent study notably includes randomizing the workers in a treatment and a control group, which improves the validity of a causal interpretation. Shearer concludes that the incentive effect of performance pay is 20%, which is very similar to the results presented in Lazear (2000).

Another paper which analyzes work in the agricultural sector is Bandiera et al. (2007). In contrast to other contributions introduced in this section, it is the wage scheme of managers,

[8] The workers' ability in this study is captured by workers' fixed effects.

not the workers, which varies in this study. It switches from an hourly wage to a piece rate, while the fruit pickers on the farm are paid a piece rate during the whole study. In this setting, managers influence the final output by organizing the daily work as well as by selecting the workers. The authors identify a productivity increase by 21% due to the change in compensation scheme.

Griffith and Neely (2009) examine performance pay which is based on the so-called 'Balanced Scorecard'[9] rather than on a piece-rate. The study analyzes its effect on branch performance of a heating product distributor. It presents an ambiguous conclusion: The introduction of performance pay caused an increase in sales, but also an increase in costs. The paper also points out that the new payment regime had a positive effect on branches with more experienced managers.

Among the papers which illustrate negative consequences of incentivized contracts is Larkin (2014). The author analyzes the introduction of a nonlinear incentive scheme for sales personnel in a software company. He illustrates that the employees react by maximizing their own income. Such behavior results in mispricing and costs the company 6%-8% of revenue. A study by Courty and Marschke (2004) considers the introduction of explicit nonlinear monetary incentives for teachers in a job training program. They show that the program causes increased effort in the measurement period, but also lowers the quality of the training.

Another negative aspect of performance pay is pointed out by Ariely et al. (2009). The study shows how stronger incentives can lead to worse performance and, therefore, challenges the assumption that a higher motivation always improves performance. However, it is important to note that the authors explicitly consider extraordinarily high monetary rewards[10]. Further, the authors base their research on a series of laboratory experiments, a methodology which needs to be viewed with caution in the considered field of research for reasons outlined earlier in this section.

[9] The Balanced Scorecard is a popular way to measure business performance and has been developed by Kaplan and Norton (1992). It includes a range of financial and operational indicators.

[10] While the study makes a relevant point, extraordinary high incentives are not the standard case and not the focus of the thesis.

2.3. Related empirical literature on task approach and ONET

The type of work conducted in the company determines which measure is available to assess performance. The measure, in other words, depends on the content of the work. A promising approach to analyzing this content is the so-called 'task approach.' This concept originates from a line of literature in the field of labor economics. It defines work as a series of tasks which need to be performed to accomplish the job (Autor 2013). Tasks are activities such as performing a calculation or driving a vehicle. The concept aims to improve the traditional view of labor economics which models labor and capital as input factors being either substitutes or complements. It allows for a more flexible analysis since one particular task can be supplied by either labor or capital and this might change over time (Autor 2013). An article by Autor et al. (2003) has laid the foundation for this development in the literature. The article focuses on evolving technology and its effects on the labor market, such as changes in tasks which are required in an occupation, a change in demand for different workers and wage effects for different occupation levels. Most prominent is the 'routinization hypothesis' which claims that machines can replace human workers to perform tasks which can be classified as 'routine.' Their empirical analysis of this work is based on data from the 'Dictionary of Occupational Titles' ('DOT'), the predecessor of the ONET (U.S. Department of Labor 1991)[11]. A later contribution by Acemoglu and Autor (2011) updates the empirical methods and bases the analysis on data from the ONET[12].

Subsequent work applies the task approach to different aspects of labor economics[13]. Most of the papers examine the impact of technological advancement on the labor market from varying perspectives. Antonczyk et al. (2010) and Dustmann et al. (2009) focus on the 'polarization' of labor, i.e. the decline of middle-class jobs in relation to high-wage and low-wage occupations. Spitz-Oener (2006) examines increasing skill requirements. Gathmann and Schönberg (2010) propose the concept of 'task-specific human capital' and measure the transferability of labor market skills to explain the mobility between different jobs. Black and Spitz-Oener (2010) analyze the effect of polarization on demand for female labor. Peri and Sparber (2009) study

[11] The DOT is a publication by the U.S. Department of Labor which defines a large number of occupations in several quantitative dimensions based on information from job analysts. It was first published in 1938 and has been periodically updated until 1999.
[12] However, not every contribution employing the task approach analyzes DOT or ONET data. The task approach is a theoretical framework which can be applied to different data.
[13] Also compare Autor and Handel (2013) for an overview of this literature.

job task assignment for native and immigrant workers. Grossman and Rossi-Hansberg (2008) explore if jobs intensive in routine tasks are more suitable for international offshoring.

One way in which the thesis builds on this literature is focusing on the content of occupations. To emphasize this, it appears helpful to understand an occupation as a bundle of tasks[14]. At the same time, the approach of this thesis requires analyzing the characteristics of a given occupation, not the characteristics of the distinct tasks within the occupation, as will be further discussed in section 3.2. A second way in which the thesis builds on this literature, especially on Acemoglu and Autor (2011), is the way of developing proxies for 'routine' and 'non-routine' from the ONET data. This process will be discussed in section 3.3.

The thesis is also related to other literature which makes use of DOT and ONET data. As Handel (2016) points out, there is only a limited number of studies analyzing such data. Three prominent examples are Hutchens (1987), Feser (2003), and Hirsch (2006). Hutchens (1987) is an early contribution which analyzes data from the DOT in order to classify if a job involves a lot of repetition of tasks and is therefore easy to monitor. He then examines the influence of repetitiveness on the type of contract. Feser (2003) illustrates how the ONET can be used to group jobs based on similarities in their broad knowledge and uses these groups to analyze the type of work done in a certain region. Hirsch (2006) analyzes occupational skill requirements from ONET data to explain the gap in hourly wages of part-time and full-time workers.

2.4. Hypothesis development

This section will develop a hypothesis of the influence of routine tasks on the employment of performance pay[15]. As argued before, a company will only employ performance pay if a suitable performance measure can be developed. If the worker's contribution can be measured, in turn, depends on the intensity in routine tasks. To begin with, it needs to be clarified what defines a

[14] Another field of literature which views a job as a bundle of tasks examines the way in which tasks are combined into jobs. However, literature on so-called 'job design' (compare Gibbs et al. 2010 for a general overview) is predominantly of theoretical nature.

[15] In understanding the term 'routine,' the thesis follows the definition adopted by Acemoglu and Autor (2011). They characterize a task as being 'routine' if it requires methodological repetition and can be specified by programmed instructions. It does not demand flexibility, judgment, or adaptation to new circumstances.
Even if this thesis does not address the technological aspect of replaceability of human workers by machines as the authors do, such a definition results in precisely the attributes which are relevant for the purposes of this thesis and is, therefore, well-suited for the approach of the thesis.

suitable performance measure[16]. Two criteria are particularly important for the hypothesis development. First, the measure must capture the worker's contribution to the principal's goals. Second, the measure must exclude factors which are outside the control of the worker. The following paragraphs will relate these two criteria to the intensity in routine tasks.

Concerning the first of the abovementioned criteria, the presented principal-agent literature has illustrated how performance measures which don't accurately picture the principal's objective will hurt the company: It provides the worker with the possibility to 'game the system' (Baker 1992) and leads to the rise of the so-called 'multi-tasking problem' (Holmström and Milgrom 1991). Measuring how well a worker has contributed to this objective can be very complex depending on the occupation. One particular challenge is the existence of several performance criteria which can be relevant, such as efficiency and quality (Harris 1994). It is increasingly difficult to develop an accurate performance measure as more dimensions become relevant[17]. In routine-task-intensive occupations, the efficiency dimension tends to dominate all other aspects. Take for example production workers (windshield glass installers as analyzed in Lazear 2000): The performance can be defined by the number of correctly installed windshields per hour. Notably, the occupation does not offer much room for varying quality: A windshield is either installed correctly, or it is not. The contribution in jobs that are intensive in non-routine tasks, on the other hand, is often more difficult to evaluate. The work might even result in different types of output. Consider again the example of a chef: The quality of the food is essential to evaluate the performance, but at the same time it is highly subjective. The output of the cook's work is heterogeneous, as the dishes might be very different[18].

Turning to the second of the abovementioned criteria, it is recognized in both the economics and the accounting literature that if a measure is used to evaluate performance, it should be determined by factors that are controlled by the recipient of the evaluation (Prendergast 2011

[16] A company can employ very different types of performance measures. A call center employee, for example, can be rewarded depending on the number of calls per hour. The performance pay of a courier might depend on the on-time delivery rate.
[17] This is widely recognized by academics and business practitioners. The development of the 'Balanced Scorecard' (Kaplan and Norton 1992) can be seen as an attempt to address this issue: It broadens the focus from financial accounting measures to a wide range of financial and operational indicators which are believed to drive future performance. Notably, this instrument focuses on the performance of the whole business, rather than on measuring the contribution of the individual worker.
[18] The reasoning of the paragraph is in-line with an observation made by Landy et al. (2017). They point out that, in general, a performance measure for routine work is easily quantifiable.

for economics literature; Globerson 1985; Lynch and Cross 1991; Neely et al. 1997 for accounting literature). A performance measure that fulfills these criteria is called 'relevant' (Fortuin 1998)[19]. If the employer cannot develop a performance measure that is relevant or if the relevance of the performance measure cannot be determined, employing performance pay will not be meaningful. To determine the relevance of the measure, the principal needs to separate the impact of the worker's actions on the performance measure from the impact of external factors. In jobs intensive in routine tasks, a limited number of working steps is performed repeatedly. In occupations that are intensive in non-routine tasks, on the other hand, the agent performs a variety of very different actions in her everyday work. Hence, it is more feasible to determine the relevance of performance measure for the first type of occupations.

These two arguments result in the following hypothesis:

> H_1: Occupations which are intensive in routine tasks (non-routine tasks) are associated with a higher (lower) likelihood of employing performance pay.

Certain assumptions underlie this hypothesis development. One assumption is that the measure is given exogenously and that the firm cannot invest in improving the performance measure. In other words: A company cannot change the composition of the performance measure and 'design away' potential weaknesses of the measure. Therefore, the firm has to decide if it wants to employ performance pay based on the best available measure. Furthermore, the organization needs to behave optimally: For the two above arguments to result in the hypothesis, the principal must recognize the two described theoretical mechanisms and adjust the compensation schemes in accordance with them.

The reasoning necessary to derive the hypothesis can be found in the classical principal-agent literature (section 2.1). Yet, this section has additionally introduced some literature from the field of management accounting to illustrate the relevance of the question for both fields.

[19] Banker and Datar (1989) present an alternative phrasing: In their words, a performance measure needs to be 'precise' and 'sensitive.' The former demands that change in the measure must be primarily caused by a change in worker's effort rather than noise. The latter requires that changes in worker's effort must result in a sufficiently large movement of the measure.

Including this literature also broadens the discussion of the topic as the contributions from management accounting are often based on a different, more applied, view on the topic.

3. The data

3.1. The WERS data set[20]

The main data source is the 'Workplace Employment Relations Study' ('WERS'). This UK-wide study collects a representative sample and includes data from interviews with employers, employees, and workers' representatives. The data can generally be characterized as repeated cross-sections. WERS has been undertaken six times in the period from 1980 to 2011. The master thesis uses the most recent data from 2011. The main advantage of the WERS data is that it contains rich and detailed information about the management practices captured by the management survey. Such data is essential to perform empirical analysis in many fields of organizational economics. At the same time, it is highly sensitive and therefore often difficult to access.

The management questionnaire contains the question 'Do any of the employees in this workplace get paid by results?' A dummy is constructed based on this question. It is equal to one if the manager answers the question in the affirmative and serves as a proxy for 'company employs performance pay.' This is the best proxy available but it has its limitations since it is a very general way to ask about performance pay. Most importantly, it does not include information on the fraction of workers receiving performance pay and on the intensity of the performance pay. It also does not distinguish between individual and group performance pay. Further, it is important to note that this is a rather narrow definition of 'performance pay' compared to related studies: This question excludes raises based on subjective and relative performance evaluation as well as profit-related pay schemes.

Further, the WERS management questionnaire data set contains a variable which holds a standard occupation classification (SOC)[21] for the largest non-managerial occupation at the workplace. A verbatim description of the activities of this occupation is recorded during the management interview and coded to the SOC classification afterwards. Relevant control variables – which will be introduced in section 4.2 – are also based on this management questionnaire.

[20] This section partly relies on Biermann 2017 (p. 5).

[21] Statistical agencies and other institutions in different countries use such a formal system to classify workers into occupational categories (Bureau of Labor Statistics 2017).

A general drawback of analyzing survey data is self-reporting bias which results in a measurement error (Bound et al. 2001; Donaldson and Grant-Vallone 2002): The answers provided by the manager might be biased and not necessarily equal to the true values.

3.2. The ONET data set

A central feature of the thesis is to develop measures of the job content. For this purpose, the thesis will make use of the 'Occupational Information Network' ('ONET') relating quantitative job descriptors to occupations from the WERS. This procedure has been popular among some papers employing the task approach to labor markets as described in chapter 2.

The ONET is the main source of occupational information in the US. The database has been developed to replace the Dictionary of Occupational Titles (DOT) by the US Department of Labor (U.S. Department of Labor 1991). The most current version of the ONET database – version 21.2 – was released in February 2017. The theoretical framework of the ONET is called the 'ONET content model' (Peterson et al. 1995; O*NET Resource Center 2017a). It covers different domains of job characteristics, classifying occupations either by the demands placed on the workers or the type of work being done. This information is encapsulated in a quantitative dimension through variables called 'descriptors.'

The data is collected through the ONET data collection program, which uses standardized questionnaires to measure job characteristics specified by the content model. The program operates continually updating the database and replacing old ratings on a rolling basis. Most of the information is collected through a two-stage sample design: First, a random sample of firms which are expected to employ the target occupation is identified. Second, a random sample of employees ('incumbent workers') within the target occupation and target firms is selected. Figure 1 (appendix) contains an example to illustrate a questionnaire instrument.

Since the two domains 'abilities' and 'skills' are of quite abstract nature, the data creation follows a different procedure for these cases. The data is first collected through a survey of incumbents and subsequently provided to occupational analysts who create the final ratings for the descriptors. These analysts are specialists that have at least two years of working experience, have obtained a graduate degree in a relevant field such as organizational psychology and have received specific training to be able to design consistent and valid ratings (Donsbach et al. 2003).

The 277 descriptors are structured in six categories and several subcategories. Descriptors are associated with different scales such as importance or frequency and each scale is defined with a different range, e.g. 1 for ‘not important’ to 5 for ‘extremely important.’ Figure 2 (appendix) contains an example to illustrate the hierarchy in which the descriptors are organized. These descriptors are available for around 1000 occupations[22]. Occupations are incorporated in the system based on the SOC.

The ONET data has its weaknesses and three of the most important ones should be pointed out. First, some survey questions are complex and abstract and are likely to confuse a respondent (Hubbard et al. 2000; Autor 2013). Second, the documentation is partly unclear. To name one example, the only publicly available information about the sample size per descriptor and occupation states that the descriptors are based on at least 15 respondents, often many more. More precise information on the sample size per descriptor and occupation is not available. Third, while the project provides a great level of detail, the distinction between some categories is unclear, resulting in seemingly overlapping survey questions as well as descriptors (Handel 2016).

At the same time, as Handel (2016) concludes in his general evaluation of the ONET, the database presents many opportunities for academic researchers. Overall, the sampling method is a large improvement compared to the DOT or general household surveys. The author presents an analysis indicating that the limitations of the methods don’t generally threaten the validity of the ONET measures. Most importantly and as pointed out by Autor (2013), making use of ONET data adds objectivity to the process of assigning attributes to occupations, since the descriptors are carefully validated by a statistical agency rather than subjectively evaluated by the researcher.

Today, the data from the project is widely used in career counseling. Although the data source is not as popular in academia, some empirical research incorporates information from the ONET, as pointed out in section 2.1. The big scale, depth of information, and long tradition

[22] Notably, the descriptors are available for occupations, not for single tasks. This structure of the data is the reason for why the thesis delivers an analysis at the level of occupations and not at the level of the individual tasks. Importantly, the instruments in the questionnaires of the ONET ask questions about the ‘current job’ and not about separate tasks performed in this job.

make the ONET the recognized primary source of occupational information in the US. Even on a global scale, such an exhaustive source of occupational information is unique.

3.3. Constructing a proxy for intensity in routine tasks

As pointed out in the last section, one of the main drawbacks of the DOT and the ONET are the partly unprecise and overlapping definitions of the descriptors (Handel 2016). As a result, it is unclear which of the descriptors best represents a certain task construct (Acemoglu and Autor 2011, p. 1078). In other words, one can include many different descriptors to characterize if routine tasks play an important role in a certain job. In this setting, selecting the right descriptors would necessarily be based on a subjective judgment. Such judgment calls are undesirable in empirical work because they give the researcher the chance to select the data according to his or her prejudices (Autor 2013). Based on this reasoning, this thesis employs the same five job content measures and descriptors as Acemoglu and Autor (2011), as this approach is the most prominent in literature and has several advantages as will be pointed out later in this section.

The analysis includes the following five job content measures: Non-routine tasks are subdivided into cognitive-analytical, cognitive-interpersonal, and manual-physical tasks, while routine tasks are separated in cognitive and manual. Cognitive-analytical tasks require 'problem-solving, intuition, persuasion, and creativity' (Acemoglu and Autor 2011, p. 1077). These tasks are common in occupations related to 'law, medicine, science, engineering, design, and management' (ibidem). Cognitive-interpersonal tasks are characterized by interactions with other people and require social skills. Occupations which score highly on this measure include nurses and teachers. Non-routine manual tasks require situational adaptability, visual recognition, and coordination skills among others. Activities which are non-routine manual-physical include for example 'driving a truck through city traffic' or 'preparing a meal' (ibidem). The job content measures are obtained by summing the standardized task descriptors and subsequently standardizing the resulting measures (following Hardy 2015, p. 11). The job content measure 'non-routine cognitive-analytical' for example consists of three descriptors: 'analyzing data/information,' 'thinking creatively,' and 'interpreting information for others.' Each of the five job content measures will be assigned to every occupation to classify the intensity in routine and non-routine tasks in this job. Table 1 illustrates the job content measures and the corresponding descriptors.

Table 1. Job content measures

non-routine cognitive-analytical
analyzing data/information thinking creatively interpreting information for others
non-routine cognitive-interpersonal
establishing and maintaining personal relationships guiding, directing and motivating subordinates coaching/developing others
non-routine manual-physical
operating vehicles, mechanized devices, or equipment spend time using hands to handle, control or feel objects manual dexterity spatial orientation
routine cognitive
importance of repeating the same tasks importance of being exact or accurate structured versus unstructured work
routine manual
pace determined by speed of equipment controlling machines and processes spend time making repetitive motions

This approach has important advantages over alternative operationalizations of 'routine' and 'non-routine.' By considering different types of 'routine' and 'non-routine,' it allows presenting a sufficiently nuanced view. Most importantly, this operationalization takes into account if the tasks are cognitive or manual. This aspect fundamentally shapes the nature of the job and the way in which tasks can be routine or non-routine. Take for example 'non-routine manual-physical' and 'non-routine cognitive-interpersonal': Both measures are non-routine, but they are profoundly different as can be seen from the corresponding descriptors (table 1).

Two important consequences follow from this. First, since not all types of routine tasks are the same, it is not appropriate to lump all tasks together in one category by creating one task content measure for 'routine' (the same holds for 'non-routine'). Second, one should understand each of the five measures as an inseparable construct. In other words, the measure 'non-routine manual-physical' cannot be separated into two different dimensions 'non-routine' and ‘manual-physical.’ The measure rather captures the intensity of a job in non-routine tasks which can be classified as manual-physical.

An alternative operationalization would be to avoid having proxies for ‘routine’ as well as ’non-routine.’ Such an approach would combine all the available information into one variable ‘routine versus non-routine work’ which takes a value between the two extrema ‘routine’ and ‘non-routine.[23]’ The drawbacks of this approach become clear after, again, examining the definition of the task content measures as presented in table 1. The table illustrates that the non-routine measures are not simply a reversal of the routine measures as they capture information on a different type of tasks. In this sense, this design of task content measure results from the descriptors contained in the ONET[24].

3.4. Constructing a data set

To incorporate information on task content from the ONET data into the analysis of the WERS data, the two databases need to be combined, i.e. appropriate occupational attributes must be assigned to the WERS data. Both data sets include the variable ‘SOC’; this is hence the natural key variable. However, different types of occupational classification systems exist, and the two databases don’t use the same SOC. While the WERS data is based on the British UK SOC (Office for National Statistics United Kingdom 2017), the ONET follows the so-called ONET SOC (O*NET Resource Center 2017b), which is based on the American US SOC in the version of 2010. It is, therefore, necessary to develop a link between the two classification systems. This is achieved by performing the four following steps:

1.) Mapping the ONET data based on ONET SOC 2010 to US SOC 2010
2.) Transforming the resulting US SOC 2010 to a data set which follows US SOC 2000
3.) Transforming the resulting US SOC 2000 data to a data set which follows UK SOC 2000
4.) Merging the resulting ONET data which follows UK SOC 2000 with the WERS data

To perform steps one and two, a STATA code provided by the University of Warsaw (Institute for Structural Research Warsaw 2017) is applied. This code allows using different crosswalks from the original ONET data to other classification systems. In this case, it first trims the ONET

[23] This variable could also be subdivided in two measures: One referring to cognitive and one to manual tasks.
[24] In addition, this issue will be addressed by an alternative regression specification as presented in section 4.3.

SOC 2010 to obtain US SOC 2010[25]. It then transforms the results to US SOC 2000 using a crosswalk provided by the Bureau of Labor Statistics (Bureau of Labor Statistics 2017a).

In step three, the resulting US SOC 2000 data is mapped to UK SOC 2000. The necessary crosswalk is provided by Anna Salomons, an associate professor at Utrecht University, who has developed a mapping system using the online coding tool CASCOT[26] and manually testing the CASCOT results (this crosswalk is used e.g. in Goos et al. 2009).

This allows merging the ONET and the WERS data in a fourth step, using UK SOC 2000 as a key for matching. The result is a data set which assigns occupational attributes to the WERS data. A table with the summary statistics of the resulting data will be presented after the discussion of the control variables (table 2, section 4.2).

The mapping between the different classification systems is not always unambiguous, i.e. a code in one classification system might have multiple counterparts in another system. Three cases must be distinguished. First, if the original code translates into multiple target codes, each of the target codes will be assigned the attribute values of the original code. Second, if multiple original codes translate to one target code, the target code will be assigned the average attribute values of the original codes. Third, if multiple original codes translate to multiple target codes, each of the target codes will be assigned the average attribute values of the original codes.

To illustrate the merging process, the following paragraphs will provide an example of one occupation and one ONET descriptor. The occupation 'sociologist' is classified by the ONET 2010 code 19-3041.00. The occupation has a value of 4.32 for the ONET descriptor that captures to which extent thinking creatively is required in an occupation (descriptor code 4.A.2.b.2, scale from one to five). The corresponding US SOC 2000 code is equivalent to the ONET SOC 2010 minus the last two digits: 19-3041 (transformation step one; one-to-one-match; descriptor value remains 4.32). Since the classification is the same for US SOC 2010 and US SOC 2000, the next transformation step is equally simple: The code 19-3041 remains the same in

[25] The ONET SOC contains the 6-digit code of the US SOC and adds a 2-digit extension, which allows for a more detailed differentiation.

[26] The 'Computer Assisted Structured Coding Tool' ('CASCOT') is designed to convert text information – in this case US SOC labels – to UK SOC codes (Warwick Institute for Employment Research 2017).

the US SOC 2000 classification (transformation step two; one-to-one-match; descriptor value remains 4.32).

The next step is transforming this code to UK SOC 2000. According to the applicable crosswalk, the US code 19-3041 corresponds to the UK code 2322. Since the UK system is less detailed, the UK code ‘2322: Social Science Researcher’ combines the US code for seven different occupations: ‘Economists,’ ‘Sociologists,’ ‘Anthropologists and Archeologists,’ ‘Geographers,’ ‘Historians,’ ‘Political Scientists,’ and ‘Social scientists and related workers, all other.’ This step is, therefore, a many-to-one match and the UK code ‘2322 Social Science Researcher’ is assigned the average descriptor value of ‘thinking creatively’ of the seven US codes which equals 4.19 (transformation step three).

In the last step, the value of the ONET descriptor is related to the workplaces in the WERS data: Two companies in the WERS data are classified to employ social science researchers as the largest non-managerial occupation at the workplace: The workplaces with the unique identifier 1116013 and 2005011 are assigned the value 4.19 for ‘thinking creatively’ (transformation step four).

4. Econometric analysis

4.1. Identification strategy

The master thesis aims to explain why some companies employ performance pay while others don't by analyzing the task content of the largest occupation at the workplace. To do so, it develops an identification strategy using performance pay as a dependent variable. The variable is limited in the sense that it is binary: A firm either employs performance pay or it does not. The independent variables include the five job content measures as developed in section 3.3 as well as relevant controls. The empirical analysis, therefore, estimates the following equation:

$$payment\ by\ results_i = \beta_0 + \sum_{j=1}^{5} \beta_j\, job\ content\ measure_{i,j} + \sum_{j=6}^{n} \beta_j \boldsymbol{X}_{i,j} + u_i$$

where *i* relates to the company and *j* stands for one of the independent variables. The vector of independent variables other than the job content measures is denoted by ***X*** and varies depending on the model specification.

To analyze the influence of the five job content measures on the employment of performance pay, the thesis will introduce a series of regression models. The models will be estimated by ordinary least squares. The first model includes only the five job content measures as independent variables. This 'naïve' model is likely to uncover a spurious correlation between performance pay and the job content measures. Therefore, different blocks of controls are added gradually. Such a procedure, often referred to as hierarchical regression or nested regression analysis, allows analyzing if the relationship between performance pay and the job content measures is stable across specifications or if the inclusion of other predictors mediates this relationship. Furthermore, it allows evaluating if the increment in explained variability obtained by adding a new set of controls is significant (Clogg et al. 1995).

In the first step, a set of controls is added which captures the operating environment of the firm. Second, another set of controls is included which contains relevant characteristics of the workforce. In steps three and four, dummies are incorporated which indicate the industry and the region of a company. The last specification is the full model.

Due to missing values, gradually adding controls will reduce the number of the observations available for a given model. As a result, the change of a coefficient is hard to interpret: It could be caused by the change of the sample rather than the added controls. Hence, for a valid model comparison, the models must be estimated on the same sample (Clogg et al. 1995). I therefore only include firms which are available for the full model in all the reduced models.

Again, an important assumption is that firms make optimal decisions. Thus, decision makers recognize that performance pay will influence firm performance which depends on firm characteristics as captured by the independent variables and act in accordance to this. The outcome of the decision can be observed in the data, i.e. a firm employs performance pay or not.

4.2. Choice of control variables

This thesis includes four sets of controls which are expected to influence the firm's decision to employ performance pay[27]. The first set of controls contains aspects of the operating environment of the firm. To begin with, the number of competitors is likely to influence performance pay. If one assumes that performance pay is a good management practice, higher competition will tend to drive the less efficient firms out of the market. Bloom et al. (2009) deliver empirical evidence for the correlation between good management practices and a measure of competition intensity (also compare Brown and Heywood 2002). Furthermore, Bloom et al. (2009) find that firms tend to be better managed if companies are more international[28]. To acknowledge this aspect, the thesis includes two controls: First, a dummy which indicates if a company is predominantly foreign owned, and second, a variable which captures how international the market for the main product is[29]. Introducing performance pay might further be associated with additional costs either through lower quality or increased expenditures due to additional monitoring because pay for performance often puts a stronger emphasis on quantity than quality (Freeman and Kleiner 2005; Courty and Marschke 2004 for empirics). This aspect is accounted for by including a variable which indicates how important quality is to the firm.

[27] The choice of control variables is partly based on Pendleton et al. (2009), the wording of these paragraphs partly relies on Biermann (2017).
[28] Captured by a categorical variable with the categories 'local firms,' 'exporter,' and 'multinational subsidiaries.'
[29] Captured by a categorical variable with the categories 'local,' 'regional,' 'national' and 'international.'

The second set of controls contains relevant characteristics of the workforce. First, the number of employees in the institution is relevant since bigger firms can spread the costs of implementing performance pay over a larger number of employees (Heywood et al. 1997). Second, the model includes the proportion of female workers and part-time workers as previous literature has argued that these characteristics are related to performance pay (Heywood et al. 1997; Brown 1990). Third, the proportion of union members is added as a control variable since unions are expected to oppose performance pay. The reason is reduction of wage inequality being one of the unions' main objectives (Slichter et al. 1960 as well as Hayter 2011 for theory; Gosling and Machin 1995 for empirics). At the same time, pay schemes based on individual performance rather than fixed pay schemes increase within-firm wage inequality (Barth et al. 2009). Fourth, communication between the managers and the workers can reduce risks associated with performance pay (Levine 1990). This aspect is captured by a dummy equal to one if the company organizes meetings between the workers and the managers. In addition, the data set allows controlling for the region in the UK and the industry of the company (third and fourth set of controls). I expect the measurability of performance and, therefore, the likelihood of performance pay to vary not only across occupations but also across industries.

Another aspect that is expected to influence the employment of performance pay is intrinsic motivation. Pay for performance is less attractive if the workforce is highly intrinsically motivated, as performance pay is an external motivator which is a substitute for internal motivators (Austin and Larkey 2002). Furthermore, if the workforce is intrinsically motivated, this motivation might be crowded out by performance pay (Frey and Oberholzer-Gee 1997; Deci and Ryan 1985). Intrinsic motivation is therefore expected to be negatively correlated with payment by results. At the same time, intrinsic motivation is correlated with the job content measure as I expect jobs intensive in non-routine tasks to be more fulfilling and workers in these occupations, therefore, more likely to be highly intrinsically motivated. However, the data set contains no variable which can serve as an appropriate proxy for internal motivation. As a result, the estimation might suffer from an omitted variables bias[30]. The following table presents the summary statistics.

[30] This relationship results in a downwards bias for non-routine job content measures and upwards bias for routine job content measures.

Table 2. Summary statistics full sample

Panel A*	Mean	S.d.	Min	Max	N
payment by results	0.26	0.44	0	1	2680
importance output quality	4.12	0.99	1	5	1793
number competitors	2.53	0.58	1	3	1797
foreign owned	0.16	0.37	0	1	1829
international market	2.28	1.15	1	4	1805
firm size	449.3	1213.5	5	20746	2680
proportion part time	0.27	0.26	0	1	2646
proportion women	0.52	0.28	0	1	2654
proportion union members	0.21	0.30	0	1	2117
meetings	0.84	0.35	0	1	2674
Panel B**	**Mean**	**S.d.**	**Min**	**Max**	**N**
non-routine cognitive-analytical	9.45	1.47	5.77	13.2	2669
non-routine cognitive-interpersonal	9.33	1.24	6.44	12.85	2669
non-routine manual-physical	9.26	2.63	4.54	16.85	2669
routine cognitive	11.41	1.04	7.95	13.52	2669
routine manual	7.28	1.79	3.62	12.2	2669

* Furthermore, the data set contains information about the industry and the location of the firm as well as the main occupation in the firm. This is captured by the 'Standard Industry Classification' ('SIC'), codes for regions in the UK and the SOC for the largest occupational group, respectively. These variables are measured on a nominal scale. Further details can be found in table 6 (appendix).

** This panel presents the non-standardized values of the job content measures. The subsequent empirical analysis uses the standardized values. Naturally, the standardized values have a mean of 0 and a standard deviation of 1.

Panel A contains the variables from the WERS data set, which includes the dependent variable, payment by results, as well as the control variables. The table illustrates that most firms don't pay their employees by results: Only roughly a quarter of the companies employ performance pay[31]. The average company in the sample has indicated that quality of the products is important (4.12 on a 1 to 5 scale), it operates in a rather competitive environment (2.53 on a 1 to 3 scale) and serves a regional or national market. Only 16% of the companies are foreign owned. The average firm employs 449.3 workers; the large standard deviation and the big range indicate that companies of very different sizes are included in the sample. The workforce

[31] The discrepancy between this value and the levels of performance pay mentioned in the introduction has two reasons: First, this data refers to firms employing performance pay, not employees covered by performance pay. Second, the thesis employs a rather narrow definition of performance pay, resulting from the analyzed data.

of the average company looks as follows: 27% are part-time workers, 52% women and 21% union members. Most companies (84%) organize meetings between workers and their supervisors. In addition, dummies for the region in the UK and the industry are available. Further information about these dummies and all other WERS variables can be found in table 6 (appendix).

Panel B presents the main explanatory variables: the job content measures constructed from the ONET. Directly comparing the statistics across the five measures is not meaningful, since they are constructed based on different descriptors. Figures 3-7 (appendix) present histograms which illustrate the distribution of the five measures across firms. One should note that non-routine manual-physical consists of four descriptors, while the other measures include only three. Further, all job content measures are standardized for the subsequent analysis.

Some of the variables are available for all 2680 firms in the sample. Others have considerably fewer observations: Only 1793 workplaces have answered the question concerning the importance of output quality. The subsequent regression analysis will include only 1477 of the 2680 firms: These are the observations without missing values for any of the relevant variables. The reason for the reduced sample is the hierarchical regression which requires analyzing the same observations in all models to make the models comparable. Hence, workplaces which are dropped from the full model due to missing values are excluded from the whole analysis. Section 4.4 will further address this issue.

The following table presents an extract of the correlation matrix. The full correlation matrix can be found in table 7 (appendix).

Table 3. Extract of the correlation matrix: Pearson's r

	PBR	NRCA	NRCI	NRMP	RC	RM
PBR	1					
NRCA	0.07**	1				
NRCI	0.02	0.64***	1			
NRMP	-0.09***	-0.48***	-0.45***	1		
RC	0.07**	0.35***	0.15***	-0.38***	1	
RM	-0.04	-0.58***	-0.52***	0.79***	-0.25***	1
quality	0.01	-0.04	0.01	-0.04	-0.06*	-0.002
competitors	0.08***	-0.01	0.02	-0.04	-0.03	-0.01

foreign	0.11***	0.04	-0.08**	0.06*	0.04	0.08***
inter. market	0.13***	0.15***	-0.10***	0.02	0.11***	0.13***
firm size	0.05*	0.13***	0.06**	-0.07**	0.09***	-0.04
part-time	-0.12***	-0.20***	0.15***	-0.18***	-0.12***	-0.16***
women	-0.08**	-0.005	0.22***	-0.45***	0.05*	-0.41***
union	-0.04	0.03	-0.02	0.15***	0.02	0.09***
meeting	0.07**	0.06**	0.02	-0.08**	0.03	-0.06*

Variables are abbreviated due to reasons of space: PBR: payment by result, NRCA: non-routine cognitive-analytical, NRCI: non-routine cognitive-interpersonal, NRMP: non-routine manual-physical, RC: routine cognitive, RM: routine manual. This table presents an extract of the correlation matrix which focuses on the dependent variable and the five main explanatory variables. The full correlation matrix can be found in table 7 (appendix).
*, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Table 3 is a starting point for examining the relationship between performance pay and the main explanatory variables. Among these five variables, non-routine manual-physical shows the strongest correlation with performance pay (-0.09), followed by non-routine cognitive-analytical and routine cognitive (both 0.07). It is furthermore noticeable that some of the independent variables are highly correlated. All the strong correlations occur among the main explanatory variables. This issue will be further discussed in section 4.4.

4.3. Regression results and interpretation

The following table presents the regression results.

Table 4. Regression results OLS: Baseline specification

	payment by result				
	(1)	(2)	(3)	(4)	(5)
non-routine cognitive-analytical	0.051**	0.022	-0.008	-0.005	-0.018
	(0.019)	(0.020)	(0.021)	(0.021)	(0.024)
non-routine cognitive-interpersonal	-0.031	-0.012	0.006	0.007	0.032
	(0.019)	(0.020)	(0.020)	(0.020)	(0.022)
non-routine manual-physical	-0.072***	-0.060**	-0.074***	-0.071**	-0.036
	(0.021)	(0.021)	(0.022)	(0.022)	(0.023)
routine cognitive	0.010	0.010	0.008	0.009	-0.008
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
routine manual	0.054*	0.028	0.018	0.023	-0.009
	(0.022)	(0.022)	(0.023)	(0.023)	(0.025)
importance output quality		-0.001	-0.004	-0.004	0.007
		(0.013)	(0.013)	(0.013)	(0.013)
number competitors		0.071**	0.063**	0.059**	0.064**
		(0.022)	(0.022)	(0.022)	(0.022)

foreign owned		0.125***	0.113**	0.107**	0.055
		(0.035)	(0.035)	(0.035)	(0.035)
international market		0.035**	0.015	0.012	0.017
		(0.012)	(0.013)	(0.013)	(0.013)
firm size			0.014	0.018	0.025
			(0.014)	(0.015)	(0.015)
proportion part time			-0.113*	-0.107	-0.165**
			(0.055)	(0.055)	(0.056)
proportion women			-0.142*	-0.136*	-0.010
			(0.058)	(0.058)	(0.065)
proportion union members			-0.144*	-0.128*	-0.057
			(0.057)	(0.057)	(0.061)
meetings			0.064*	0.065*	0.070*
			(0.030)	(0.030)	(0.029)
dummies region				Yes	Yes
dummies industry					Yes
constant	0.340***	0.066	0.206*	0.099	-0.016
	(0.013)	(0.074)	(0.087)	(0.099)	(0.107)
observations	1477	1477	1477	1477	1477
R^2	0.02	0.04	0.06	0.07	0.14

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. The firm's size is measured in thousands of employees.

Model 1 in table 4 presents a starting point estimating performance pay as a function of the five job content measures. The association between the two job content measures and the dependent variable is promising since their impact is statistically significant and the direction of the impact is in-line with the theoretical prediction: 'routine manual,' 'non-routine manual-physical' (in the following: 'NRMP'). 'Non-routine cognitive analytical' appears to have a significant impact, but the sign of the coefficient contradicts the hypothesis from chapter 2. The remaining two job content measures are not statistically significant.

Column 2 in table 4 introduces controls for the operating environment of the firm. In the first place, these controls impact the influence of 'non-routine cognitive analytical' and 'routine manual.' The coefficient size of these two job content measures decreases, and they become insignificant. The effects of these predictors remain insignificant in all the following models. The explanatory power of the job content measure NRMP is mediated only slightly: The size of the coefficient declines by about 17 percent, suggesting that some of the association between performance pay and NRMP is due to characteristics of the operating environment of the firm correlated with NRMP. In other words, the previous specification suffered from an omitted variable bias. One of the controls in this bundle is the number of competitors. As presented in the correlation matrix in table 7 (appendix), the number of competitors is positively correlated with performance pay and negatively correlated with NRMP. Omitting this aspect, therefore, leads to a downwards bias. Hence, the estimated NRMP-coefficient in column 1 is more negative than the 'true' coefficient[32]. However, the effect remains statistically significant (at a 0.01% level) and negative. In other words, workplaces, where the job of the largest occupational group is characterized by non-routine manual-physical tasks, are less likely to employ performance pay (as hypothesized). The effect is also economically relevant: A one-standard deviation increase in NRMP is associated with a 6 percentage points decrease in the likelihood of employing performance pay.

Model 3 additionally accounts for characteristics of the workforce. The impact of NRMP is not altered by the additional controls: The coefficient remains significant, and the change in coefficient size even suggests a slightly stronger effect than in column 2. This indicates that NRMP has a robust impact beyond characteristics of the operating environment and the workforce of the firm. Column 4 includes controls for the region of the workplace. The effect of NRMP remains almost unchanged: It stands out as a strong predictor of payment by results. Column 5 adds industry dummies to the regression specification. The NRMP coefficient drops by roughly 50 percent compared to the previous model and becomes insignificant at any conventional significance level (p-value of 0.12).

The change in the NRMP coefficient as a reaction to incorporating industry dummies in the regression requires an economic interpretation. Simply dismissing NRMP as a spurious result of the industry might ignore an interesting mechanism revealed by this finding. A potential explanation is that NRMP and industry are closely related, making it difficult to determine which of the two factors impacts performance pay. A simple linear regression of NRMP on industry dummies (unreported) helps to analyze this issue. The R^2 of this regression indicates that over 40% of the variation of NRMP can be explained by the industry (R^2: 0.420), supporting the view that these two aspects strongly influence each other. In other words, the amount of non-routine physical tasks depends partly on the industry. Based on this evidence, the job

[32] This reasoning should be understood as a rough guide to thinking about this bias: Strictly speaking, all other explanatory variables which are correlated with NRMP will also influence the bias.

content measure can be interpreted as the mechanism underlying the impact of the industry on performance pay. Following this interpretation, analyzing job content measures might be a fruitful approach to analyzing the way in which industry influences the employment of performance pay.

Turning to control variables of the estimation, two variables appear to be strong predictors and robust across all specifications. First, the likelihood of performance pay is higher for firms in more competitive markets. Second, regular meetings between workers and supervisors are positively associated with performance pay (both as hypothesized). Another aspect which is significant in the full model is the proportion of part-time workers which negatively influences the likelihood of performance pay[33].

Furthermore, it is striking that three control variables are significant in column 4 and turn insignificant after including industry dummies and therefore show the same pattern as NRMP: The dummy capturing if a company is predominantly foreign owned as well as the proportion of women and union members. This finding is in-line with the interpretation of the difference in the NRMP coefficient between columns 4 and 5. The industry appears to be an outstandingly strong predictor of performance pay. It is also strongly related to other characteristics of the firm – including ownership structure and workers' characteristics (gender and union membership) – and is, therefore, a dominant aspect of the relationship between performance pay and these factors.

The fact that the job content measure manual-physical has a robust significant impact while other job content measures do not is somewhat surprising. One explanation might be a factor which plays an overall dominating role in the decision to employ performance pay but cannot be captured by the data. The effect of a job content measure could only unfold if it is not overshadowed by such a dominant factor. Suppose this dominating factor is highly important for occupations with extreme scores on some job content measures but less relevant for the manual-physical dimension. One example is ethical considerations. Many people might oppose

[33] While a similar pattern has been found by earlier empirical studies (Heywood et al. 1997 and Pendleton et al. 2009 for British data; Drago and Heywood 1995 for Australian data; Barth et al. 2009 for Norwegian data), the result remains surprising and it is difficult to find an economical explanation. If anything, Brown and Heywood (2002) argue, one would expect the relationship to move in the opposite direction. Since part-time employees are likely to be less committed to the organization and long-term relationships are less likely, the decision makers in the firm might feel the need to motivate them through performance pay (Brown and Heywood 2002, p. 59).

payment for performance for certain jobs. This might be particularly important for occupations which score highly on the interpersonal measure (including teachers and nurses). It might also be relevant for some occupations on the tail end of the distribution of the analytical job content measure (such as doctors and lawyers). At the same time, it is arguably not the case for the NRMP measure (occupations with high scores include restaurant chefs and truck drivers). As a result, only the effect of the latter measure can unfold and becomes observable in the data.

Another explanation concerns the nature of available information in the WERS, which is associated with some inaccuracy. First, performance pay is captured by a dummy variable. Ideally, one would access information on the fraction of workers receiving performance pay and on the intensity of the performance pay. Second, the data only makes it possible to observe the relationship between the job content of the biggest occupational group and employment of performance pay in the whole company. Ideally, the econometric analysis would relate the job content of every occupation in the organization with information on performance pay for this occupation. These limitations of the data make it likely that an effect of the job content measure can only be detected if this effect is statistically large. Therefore, analyzing the described ideal data set might reveal a significant impact of the other job content measures.

As pointed out in section 3.3, the regression specification contains explanatory variables which capture the intensity in non-routine tasks and others which capture the intensity in routine tasks (for the same category of tasks). One might be concerned that this results in a misspecification as the regression includes multiple explanatory variables which measure the same underlying construct. To address this issue, table 5 contains an alternative specification. This specification excludes the two variables containing information on the intensity in routine tasks. All non-routine measures are included in this estimation.

Table 5. Regression results OLS: Alternative specification – only non-routine measures

	payment by result				
	(1)	(2)	(3)	(4)	(5)
non-routine cognitive-analytical	0.042*	0.017	-0.011	-0.010	-0.017
	(0.017)	(0.018)	(0.020)	(0.020)	(0.022)
non-routine cognitive-interpersonal	-0.039*	-0.015	0.004	0.005	0.032
	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)
non-routine manual-physical	-0.040**	-0.045**	-0.066***	-0.060***	-0.038*
	(0.014)	(0.014)	(0.016)	(0.016)	(0.017)
controls I: operating environment		Yes	Yes	Yes	Yes

controls II: characteristics workforce			Yes	Yes	Yes
controls III: dummies region				Yes	Yes
controls IV: dummies industry					Yes
observations	1477	1477	1477	1477	1477
R^2	0.01	0.04	0.06	0.07	0.14

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. For clarity, the values of the single control variables are not presented. The identification strategy and the sets of control variables are identical with the baseline regression.

Overall, the results are very similar to the baseline specification in table 4: Non-routine cognitive-analytical and non-routine cognitive-interpersonal don't have a significant effect except for in the first model. NRMP, on the other hand, is significant in columns 1 to 4 and even after the introduction of industry dummies in column 5. Turning to the coefficient size of NRMP, table 5 presents a coefficient which is less negative (i.e. closer to zero) than in the baseline specification. This indicates an omitted variable bias, as two variables have been excluded from the model. For this reason, I retain the baseline specification as presented in table 4 as my main specification [34] . This alternative specification, however, indicates that the presented interpretation is valid. Further, column 5 of table 5 indicates that the former interpretation of the significant effect of NRMP is, if anything, rather conservative: The coefficient size is very similar to the one presented in the baseline specification (table 4 column 5) and the coefficient is now significant due to the lower standard error.

Another potential concern is the exogeneity of the main explanatory variables. The presented discussions have argued that the performance measure, which results from the job content, is a factor which determines performance pay. The job content and the resulting performance measure have been assumed to be exogenously given to the company. One might question this assumption. After all, it is the organization itself which creates the jobs in the company.

To analyze this issue, it is useful to consider the concept of 'job design.' This term has been established in literature to describe the process of bundling tasks in an organization into jobs

[34] The second reason is of rather theoretical nature: As argued in section 3.3, it follows from the way the job content measures are constructed that the different measures do not have the same underlying construct, and therefore all five measures should be included.

(compare Gibbs et al. 2010 for a general overview). Assuring the measurability of performance could be one potential aim during the process of designing jobs. In the most extreme case, employing performance pay might be a major concern for some firms. As a result, these firms would design jobs in such a way that performance is easily measurable (at least for some jobs in the firm) and, therefore, performance pay can be employed. If firms behaved in such a way, using the performance measure as an explanatory aspect for performance pay would not be a valid approach.

However, one typically thinks of a firm employing performance pay to improve the company's performance rather than employing performance pay as a goal in itself. In this sense, other aspects are expected to be paramount in the process of designing jobs. Two considerations seem to be particularly crucial. First, firms will bundle tasks which complement each other (such as research and teaching for professors, Lazear and Oyer 2007). Second, workers' skills are heterogeneous. Hence, the firms will aim to make use of the workers' comparative advantage in performing the tasks (Rosen 1978) and design jobs accordingly.

In summary, the presented models illustrate that the NRMP job content measure has a negative influence on performance pay as predicted by theory. The relationship is robust across the first four specifications and is mediated when industry dummies are included in the regression. None of the other job content measures appear to have a significant effect on performance pay which is robust across specifications.

4.4. Regression diagnostics and robustness checks

The purpose of this section is to detect any characteristics of the data which might lead to biased results and call the trustworthiness of the conclusions into question. The section refers to the underlying assumptions of the model. In the case of the OLS regression, these assumptions are often called the Gauss-Markov assumptions. However, the section only loosely bases the analysis on these assumptions, understanding them as benchmarks for discussion. One reason is that the assumptions refer to ideal characteristics of the data, which are rarely met by real data. Furthermore, there might be characteristics of the data different than the classical assumptions which are worth discussing.

First, a natural concern is that an OLS model might deliver misleading results in the case of a binary dependent variable. One classical assumption underlying OLS is linearity in parameters.

This is clearly violated in the case of a dependent variable which takes the values zero and one, leading to a case where the OLS model could provide predictions lying outside of the meaningful range of zero and one. Previous literature (e.g. Horrace and Oaxaca 2006) has indicated that a logit model delivers more accurate results than a linear probability model. Therefore, the baseline specification is estimated using a logit estimation. The results of this model are presented in table 8 (appendix). The table illustrates that the general conclusions from the OLS estimation concerning the significance levels similarly hold in the logit estimation: None of the coefficients of interest is significant in one specification but insignificant in the other. To compare the coefficient size of the two estimation methods, table 9 (appendix) contains the average marginal effects of the explanatory variables from the full model of the logit estimation (table 8 column 5). The size of the coefficients from the two estimation techniques is very similar. Focusing on the main coefficients of interest, both OLS and logit present coefficients which are identical to the first two decimal places. Therefore, the conclusions from both estimation techniques are the same and the relationship appears robust across these two estimation methods.

Second, a standard OLS assumption is that errors are normally distributed. This assumption influences the standard errors associated with the coefficients which are required to analyze exact inference based on t-statistics[35]. The Shapiro-Wilk test (Shapiro and Wilk 1965) suggests that this assumption is violated (table 10 in the appendix). This test explores the null hypothesis that the errors are normally distributed and rejects this hypothesis. However, a violation of this assumption is nowadays widely considered inconsequential for large samples (Menard 2002; Lumley et al. 2002; Wooldridge 2015, p. 155). Since this analysis examines a sufficiently large sample, this finding does not threaten the credibility of the results.

Third, OLS requires homoscedasticity, i.e. the standard deviations of the errors do not depend on the values of the predictors. Similar to the previous assumption, heteroscedasticity only affects standard errors (and hence t-values and p-values). Table 10 (appendix) presents the formal test: The Breusch-Pagan test (Breusch and Pagan 1979) has the underlying null hypothesis that the variance is constant. The test rejects this hypothesis. One way to address concerns about the lack of normality and heteroscedasticity is to estimate the standard errors

[35] Higher standard errors result in a lower absolute magnitude of t-values (negative or positive). The assumption is not required for unbiasedness of OLS, i.e. it does not influence the magnitude of the coefficients.

using robust variance estimators (first proposed by Huber 1967). As a robustness check, I have considered an OLS estimation using robust standard errors. The standard errors from this estimation are very similar to the ones from the baseline specification: None of the standard errors of the main explanatory variables deviate by more than 0.02; they are therefore unreported.

Fourth, outliers in the data might distort the estimation results. Different measures are available to analyze the influence of outliers. One way is to consider the studentized residuals. A residual is the deviation of the observed value from the estimated value. Studentizing is the procedure of dividing these residuals by an estimate of their standard deviation (in analogy with normalizing). None of the studentized residuals in the data is larger than 2.5. This measure, therefore, does not suggest the presence of outliers (unreported). A second method is to examine Cook's distance, an estimate of the influence of a data point. Influential points are outliers which additionally affect the slope of the regression line. Cook and Weisberg (1982) have suggested that values greater than one should be examined as highly influential points. This is not the case for any of the data points in the current estimation (unreported). An alternative measure of influence is DFBETA. Its logic is similar to Cook's distance, but a separate value is calculated for each regressor. The data does not contain any value with DFBETA larger than 1 (unreported); while 2 is a common cut-off value (Belsley 1980). Overall, none of these methods suggest that outliers threaten the validity of this regression analysis.

Fifth, one might be concerned that some of the independent variables are correlated. In such a case, the empirical model suffers from collinearity. If there is little variation in one independent variable that cannot mostly be explained by the variation of another independent variable, it will be difficult to estimate the effect of these variables on performance pay. Collinearity inflates the standard errors of the coefficients (and does not influence coefficient size). It is problematic only if it complicates the determination of the effect of the variables of interest. As long as the collinear variables are only control variables, collinearity is not harmful: The standard errors of the coefficients of interest are unaffected, and the virtue of the other variables as control variables is not influenced (Wooldridge 2015, p. 86). In the current model, a potential problem might be a high correlation between the different job content measures as they refer to related underlying constructs.

A starting point for examining collinearity is the correlation matrix in table 7 (appendix). It reveals a high correlation among some of the job content measures. The relationships appear to be driven by the distinction between manual and cognitive tasks. If an occupation is intensive in manual tasks, it will score higher on all measures capturing manual tasks, irrespectively of routine or non-routine. Analogously, it will score lower on all measures referring to cognitive tasks. This relationship is particularly problematic in the case of the connection between NRMP and routine manual (Pearson's r = 0.793). To address the potential issue of collinearity, table 11 (appendix) presents an alternative estimation as a robustness check. This specification excludes routine manual from the model as this variable is causing a big part of the strong correlations among the task content measures. The results are very similar to the baseline specification[36]. Overall, the results appear robust and collinearity does not threaten the credibility of the results.

Another way of analyzing the issue of collinearity are variance inflation factors (VIF). They provide information about how much the variance of each regression coefficient is inflated due to collinearity. According to a widely-used rule of thumb, a variance inflation factor larger than ten indicates excessive collinearity (O'Brien 2007). Even if this generalization might not always be appropriate (ibidem), the analysis of the VIF suggests no reasons for concerns about collinearity since all VIF values are nowhere close to this threshold (table 10 in the appendix).

Sixth, another potential concern addresses the selection of the sample. As outlined earlier, the baseline specification only uses observations which are included in the full model to allow for a valid model comparison among the different columns. This procedure leads to excluding 1192 observations from the estimation. One might be concerned that the remaining 1477 observations are not representative, which could lead to biased results. This threat occurs in particular when the dropped variables are not a random selection from the full sample but follow some systematic pattern. Consider for example that firms in a non-competitive environment are likely to refuse to answer the question about the number of competitors. Additionally, consider that these observations, which are dropped from the sample, are also

[36] Results from table 11 (appendix) are even more similar to the alternative specification which excludes the measures routine manual and routine cognitive (table 5, section 4.3). This is not surprising since the only difference between the two specifications is one explanatory variable, routine cognitive, which did not show a significant influence on performance pay in earlier specifications. For this reason, the master thesis does not present a detailed discussion of the results in table 11. For a more detailed interpretation, compare the discussion of table 5 as presented in section 4.3.

less likely to reveal a significant relationship between the job content measures and performance pay than the other observations, which remain in the sample. The combination of these two aspects will lead to biased results. In this sense, the uncovered relationships would be dependent on dropping the observations.

As a first step to examine this issue, one can compare the summary statistics for the full sample (table 2, section 4.2) with the summary statistics for the reduced sample (table 12 in the appendix). Overall, the descriptive statistics are similar for both samples. At the same time, three variables show noticeable changes: First, the proportion of firms which employ payment by results increases from 26% to 33% in the reduced sample. Second, the average firm size decreased from 449.3 to 244.9. In addition, the maximum value for firm size shows a strong decrease. The drop in average firm size is, therefore, likely due to excluding some very large companies from the sample. Third, the average proportion of union members decreases from 21% to 11%. It is important to acknowledge that the two samples show these differences, in particular, the 7 percentage points higher proportion of firms which employ payment by results. At the same time, the changes don't appear to be large enough to fundamentally question the validity of the conclusions from the regression analysis based on the reduced sample.

To provide some further evidence that excluding the observations does not change the main findings, table 13 (appendix) presents two different specifications for the 'naïve regression,' one being based on the full sample and one including only the observations from the full model (identical to table 4 column 1 in section 4.3). The comparison shows that the results are very similar for four of the five coefficients of interest. None of these four variables is significant in one specification but insignificant in the other. Some of the coefficients show a change in size, none of which is larger than 0.025. The fifth measure, non-routine cognitive-interpersonal, appears to be considerably different in the two columns: The impact is insignificant in the reduced sample, but highly significant in the full sample. This suggests that a significant effect of this measure might have been uncovered if the full sample was available for all five steps of the baseline specification[37]. I have furthermore tested if there are alternative identification

[37] However, in a specification in which all the five columns are estimated based on all available observations (instead of the same observations included in the final model) non-routine cognitive-interpersonal does not show a significant effect in any other than the first column (unreported).
Furthermore, even if the thesis neglected a present effect only because of the excluded observations, the thesis would miss an opportunity to uncover an interesting relationship. Most importantly, the robustness check does not challenge the credibility of the uncovered relationship between NRMP and performance pay.

strategies which make it possible to avoid losing such a big number of observations by excluding one of the controls from the baseline specification (unreported). There is no such meaningful specification because none of the control variables alone accounts for a big drop in available observations.

Seventh, OLS has been developed to estimate the influence of factors which are measured on a ratio scale. In the presented regression specification, three of the controls are measured on an ordinal scale: the number of competitors[38], the internationality of the product market, and the importance of output quality. As it is common in literature, I have treated these variables as continuous, even when the spacing is not equal across categories (Long and Freese 2006). I have tested an alternative specification which includes these three variables as categorical variables (in form of dummy variables) and found almost unchanged results with respect to the main explanatory variables (therefore unreported).

In summary, this section has illustrated that the main results appear to be robust. None of the discussed characteristics appears to threaten the validity of the results.

[38] With the categories 'none/organization dominates market,' 'few competitors,' 'many competitors.'

5. Conclusion

The thesis has shed light on the factors determining a company's decision to introduce performance pay by empirically analyzing which firms employ such a pay scheme. It has specifically focused on the relationship between the content of the work conducted in a firm and the employment of performance pay. The first part after the introduction has identified the classical principal-agent theory as the foundation for the theoretical reasoning of the thesis. It has furthermore discussed empirical evidence which mainly focuses on how workers react to performance pay. In addition, the task approach has been presented as a way of quantifying the content of an occupation.

Building on these streams of literature allowed for the development of a testable hypothesis which is based on the following reasoning: A company will only employ performance pay if it can appropriately measure performance. The availability of a performance measure, in turn, largely depends on the content of the work conducted in the firm. The thesis has illustrated why the intensity in routine and non-routine tasks is particularly important. The discussion has led to the following hypothesis: Occupations which are intensive in routine tasks (non-routine tasks) are associated with a higher (lower) likelihood of employing performance pay.

The third part has introduced the two relevant data sets. The 'Workplace Employment Relations Study' ('WERS') contains information on which companies employ performance pay as well as rich data on the management practices from a management survey. Data from the 'Occupational Information Network' ('ONET') includes standardized job descriptors allowing to construct job content measures which capture if an occupation is intensive in routine and non-routine tasks. The thesis has described the process of developing the five job content measures as well as the necessary steps to create one data set from the two sources.

The econometric analysis has discussed the identification strategy and the concept of the nested regression analysis. It has introduced a rich set of relevant control variables which are included in the WERS data. The empirical evidence for the tested hypothesis is mixed. While four job content measures don't show a statistically significant effect on performance pay, one measure appears to be a relevant predictor. If the main activities of the workforce are intensive in non-routine tasks which are manual-physical, the firm will be less likely to employ performance pay. The effect of NRMP is statistically significant, economically relevant and the relationship is robust across different specifications.

The industry plays an important role in the analyzed relationship: The coefficient of NRMP becomes insignificant, as industry dummies are added to the regression. I have argued that despite this finding, NRMP should not simply be dismissed as a spurious result of industry. The job content measure can be interpreted as the underlying mechanism and can contribute to understanding why the industry is such a strong predictor of performance pay.

In addition, this research has presented regression diagnostics and robustness checks to examine potential issues which might lead to biased results and call the trustworthiness of the conclusions into question. The section has discussed the Gauss-Markov assumptions, the estimation results of a logit model and the effects of a reduced sample size in a nested regression analysis. None of the discussed aspects threaten the validity of the main conclusions.

While there is some empirical evidence suggesting that workers react to performance pay, we still know little about how different factors determine a firm's decision to employ performance pay. The master thesis contributes to closing this gap in literature. It has provided empirical evidence on the relationship between firm characteristics, especially the job content of the main occupation, and the firm's decision to introduce performance pay.

Future research might focus on establishing a causal link between the explanatory factors and the employment of performance pay. Analyzing richer data might help to achieve this goal. One example is examining panel data which would allow to include fixed effects, making it possible to control for unobservable time invariant factors. Another example is analyzing a natural field experiment. Doing so can help to uncover a causal relationship by examining an exogenous variation in an explanatory variable and the resulting effect on performance pay.

References

Acemoglu, D., and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In: Card, D., and Ashenfelter, O. (Eds.). *Handbook of Labor Economics, Volume 4, Part B*, 1043-1171. Amsterdam et al.: Elsevier.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2010). Polarization and Rising Wage Inequality: Comparing the U.S. and Germany. IZA Discussion Paper no. 4842, IZA, Bonn. Retrieved from: http://ftp.iza.org/dp4842.pdf.

Ariely, D., Gneezy, U., Loewenstein, G., and Mazar, N. (2009). Large Stakes and Big Mistakes. *The Review of Economic Studies*, 76(2), 451-469.

Austin, R., and Larkey, P. (2002). The Future of Performance Measurement: Measuring Knowledge Work. In: Neely, A. (Ed.). *Business Performance Measurement: Theory and Practice*, 321-342. Cambridge: Cambridge University Press.

Autor, D. H. (2013). The "Task Approach" to Labor Markets: An Overview. *Journal for Labour Market Research*, 46(3), 185-199.

Autor, D. H., and Handel, M. J. (2013). Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, 31(1), 59-96.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4), 1279-1333.

Baker, G. P. (1992). Incentive Contracts and Performance Measurement. *Journal of Political Economy*, 100(3), 598-614.

Bandiera, O., Barankay, I., and Rasul, I. (2007). Incentives for Managers and Inequality Among Workers: Evidence from a Firm-Level Experiment. *The Quarterly Journal of Economics*, 122(2), 729-773.

Banker, R. D., and Datar, S. M. (1989). Sensitivity, Precision, and Linear Aggregation of Signals for Performance Evaluation. *Journal of Accounting Research*, 27(1), 21-39.

Barth, E., Bratsberg, B., Haegeland, T., and Raaum, O. (2009). Performance Pay and Within-Firm Wage Inequality. IZA Discussion Paper no. 4137, IZA, Bonn. Retrieved from: http://anon-ftp.iza.org/dp4137.pdf.

Belsley, D. A., Kuh, E., and Welsch, R. E. (2005). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity.* Hoboken: John Wiley & Sons.

Biermann, J. (2017). Performance Pay and Firm Characteristics – An Empirical Analysis. Unpublished seminar paper.

Black, S. E., and Spitz-Oener, A. (2010). Explaining Women's Success: Technological Change and the Skill Content of Women's Work. *The Review of Economics and Statistics*, 92(1), 187-194.

Bloom, N., Genakos, C., Sadun, R., and Van Reenen, J. (2009). Does Management Matter? New Empirics and Old Theories. Manuscript, London School Economics/Stanford University.

Bloom, N., and Van Reenen, J. (2011). Human Resource Management and Productivity. In: Card, D., and Ashenfelter, O. (Eds.). *Handbook of Labor Economics, Volume 4, Part B*, 1697-1767. Amsterdam et al.: Elsevier.

Bound, J., Brown, C., and Mathiowetz, N. (2001). Measurement Error in Survey Data. In: Heckman, J. J. and Leamer, E. (Eds.). *Handbook of Econometrics, Volume* 5, 3705-3843. Amsterdam et al.: Elsevier.

Breusch, T. S., and Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, 47(5), 1287-1294.

Brown, C. (1990). Firms' Choice of Method of Pay. *Industrial and Labor Relations Review*, 43(3), 165-182.

Brown, M., and Heywood, J. S. (2002). *Paying for Performance: An International Comparison*. New York: M.E. Sharpe.

Bureau of Labor Statistics (2017a). Crosswalks Between the 2010 SOC and Systems Used by Other Federal and International Statistical Agencies. Retrieved from: https://www.bls.gov/soc/soccrosswalks.htm.

Bureau of Labor Statistics (2017b). Standard Occupational Classification. Retrieved from: https://www.bls.gov/soc/.

Clogg, C. C., Petkova, E., and Haritou, A. (1995). Statistical Methods for Comparing Regression Coefficients Between Models. *American Journal of Sociology*, 100(5), 1261-1293.

Cook, R. D., and Weisberg, S. (1982). *Residuals and Influence in Regression*. New York: Chapman and Hall.

Courty, P., and Marschke, G. (2004). An Empirical Investigation of Gaming Responses to Performance Incentives. *Journal of Labor Economics*, 22(1), 23-56.

Deci, E. L., and Ryan, R. M. (1985). The General Causality Orientations Scale: Self-Determination in Personality. *Journal of Research in Personality*, 19(2), 109-134.

Donaldson, S. I., and Grant-Vallone, E. J. (2002). Understanding Self-Report Bias in Organizational Behavior Research. *Journal of Business and Psychology*, 17(2), 245-260.

Donsbach, J., Tsacoumis, S., Sager, C., and Updegraff, J. (2003). *O*NET Analyst Occupational Abilities Ratings: Procedures*. Raleigh, N.C.: National Center for O*NET Development. Retrieved from: https://www.onetcenter.org/dl_files/AnalystProc.pdf.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the German Wage Structure. *The Quarterly Journal of Economics*, 124(2), 843-881.

Feser, E. J. (2003). What Regions Do Rather than Make: A Proposed Set of Knowledge-Based Occupation Clusters. *Urban Studies*, 40(10), 1937-1958.

Fortuin, L. (1988). Performance Indicators – Why, Where and How? *European Journal of Operational Research*, 34(1), 1-9.

Freeman, R. B., and Kleiner, M. M. (2005). The Last American Shoe Manufacturers: Decreasing Productivity and Increasing Profits in the Shift from Piece Rates to Continuous Flow Production. *Industrial Relations: A Journal of Economy and Society*, 44(2), 307-330.

Frey, B. S., and Oberholzer-Gee, F. (1997). The Cost of Price Incentives: An Empirical Analysis of Motivation Crowding-Out. *The American Economic Review*, 87(4), 746-755.

Gathmann, C., and Schönberg, U. (2010). How General Is Human Capital? A Task-Based Approach. *Journal of Labor Economics*, 28(1), 1-49.

Gibbs, M., Levenson, A., and Zoghi, C. (2010). Why Are Jobs Designed the Way They Are? In: Polachek, S. W., and Tatsiramos, K. (Eds.). *Jobs, Training, and Worker Well-Being*, 107-154. Bingley: Emerald Group Publishing Limited.

Globerson, S. (1985). Issues in Developing a Performance Criteria System for an Organization. *International Journal of Production Research*, 23(4), 639-646.

Goos, M., Manning, A., and Salomons, A. (2009). Job Polarization in Europe. *The American Economic Review*, 99(2), 58-63.

Gosling, A., and Machin, S. (1995). Trade Unions and the Dispersion of Earnings in British Establishments, 1980-90. *Oxford Bulletin of Economics and Statistics*, 57(2), 167-184.

Griffith, R., and Neely, A. (2009). Performance Pay and Managerial Experience in Multitask Teams: Evidence from within a Firm. *Journal of Labor Economics*, 27(1), 49-82.

Grossman, G. M., and Rossi-Hansberg, E. (2008). Trading Tasks: A Simple Theory of Offshoring. *The American Economic Review*, 98(5), 1978-1997.

Handel, M. J. (2016). The O*NET Content Model: Strengths and Limitations. *Journal for Labour Market Research*, 49(2), 157-176.

Hardy, W., Keister, R., and Lewandowski, P. (2015). Redefining vs. Reallocating. Task-Driven Job Segmentation in Poland. IBS Working Paper 10/2015, IBS, Warsaw. Retrieved from: http://conference.iza.org/conference_files/worldb2015/lewandowski_p9882.pdf.

Harris, D. H. (1994). *Organizational Linkages: Understanding the Productivity Paradox*. Washington, D.C.: National Academies Press.

Hayter, S. (2011). *The Role of Collective Bargaining in the Global Economy: Negotiating for Social Justice*. Cheltenham: Edward Elgar Publishing.

Heywood, J. S., Siebert, W. S., and Wei, X. (1997). Payment by Results Systems: British Evidence. *British Journal of Industrial Relations*, 35(1), 1-22.

Hirsch, B. T. (2006). Why Do Part-Time Workers Earn Less? The Role of Worker and Job Skills. *Industrial and Labor Relations Review*, 58(4), 525-551.

Holmström, B. (1979). Moral Hazard and Observability. *The Bell Journal of Economics*, 10(1), 74-91.

Holmström, B., and Milgrom, P. (1991). Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design. *Journal of Law, Economics, and Organization*, 7, 24-52.

Holmström, B., and Milgrom, P. (1994). The Firm as an Incentive System. *The American Economic Review*, 84(4), 972-991.

Horrace, W. C., and Oaxaca, R. L. (2006). Results on the Bias and Inconsistency of Ordinary Least Squares for the Linear Probability Model. *Economics Letters*, 90(3), 321-327.

Hubbard, M., McCloy, R., Campbell, J., Nottingham, J., Lewis, P., Rivkin, D., and Levine, J. (2000). *Revision of O*NET Data Collection Instruments*. Raleigh, N.C.: National Center for O*NET Development. Retrieved from: https://www.onetcenter.org/dl_files/Data_appnd.pdf.

Huber, P. J. (1967). The Behavior of Maximum Likelihood Estimates under Nonstandard Conditions. In: Le Cam, L. M., and Neyman, J. (Eds.). *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, Vol. 1*, 221-233. Cambridge: Cambridge University Press.

Hutchens, R. M. (1987). A Test of Lazear's Theory of Delayed Payment Contracts. *Journal of Labor Economics*, 5(4), 153-170.

Institute for Structural Research Warsaw (2017). Resources. Retrieved from: www.ibs.org.pl/resources.

Kaplan, R. S., and Norton, D. P. (1992). The Balanced Scorecard: Measures that Drive Performance. *Harvard Business Review*, 70(1), 71-79.

Kerr, S. (1975). On the Folly of Rewarding A, While Hoping for B. *Academy of Management Journal*, 18(4), 769-783.

Landy, F., Zedeck, S., and Cleveland, J. (2017). *Performance Measurement and Theory*. London, New York: Taylor and Francis.

Larkin, I. (2014). The Cost of High-Powered Incentives: Employee Gaming in Enterprise Software Sales. *Journal of Labor Economics*, 32(2), 199-227.

Lazear, E. P. (1986). Salaries and Piece Rates. *Journal of Business*, 9(3), 405-431.

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

Lazear, E. P., and Oyer, P. (2007). Personnel Economics. NBER Working Paper no. 13480, NBER, Cambridge. Retrieved from: http://www.nber.org/papers/w13480.

Levine, D. I. (1990). Participation, Productivity, and the Firm's Environment. *California Management Review*, 32(4), 86-100.

Long, J. S., and Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata*, 2nd Edition. College Station, Texas: Stata Press.

Lumley, T., Diehr, P., Emerson, S., and Chen, L. (2002). The Importance of the Normality Assumption in Large Public Health Data Sets. *Annual Review of Public Health*, 23(1), 151-169.

Lynch, R. L., and Cross, K. F. (1991). *Measure up!: The Essential Guide to Measuring Business Performance*. London: Mandarin.

Menard, S. (2002). *Applied Logistic Regression Analysis*. New York: Sage Publications.

Neely, A., Richards, H., Mills, J., Platts, K., and Bourne, M. (1997). Designing Performance Measures: A Structured Approach. *International Journal of Operations and Production Management*, 17(11), 1131-1152.

O'Brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality and Quantity*, 41(5), 673-690.

Office for National Statistics United Kingdom (2017). Standard Occupational Classification 2010. Retrieved from: https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010.

O*NET Resource Center (2017a). Content Model Outline – Detailed. Retrieved from: https://www.onetcenter.org/content.html.

O*NET Resource Center (2017b). The O*NET-SOC Taxonomy. Retrieved from: https://www.onetcenter.org/taxonomy.html.

Paarsch, H. J., and Shearer, B. J. (1999). The Response of Worker Effort to Piece Rates: Evidence from the British Columbia Tree-Planting Industry. *Journal of Human Resources*, 34(4), 643-667.

Paarsch, H. J., and Shearer, B. J. (2000): Piece Rates, Fixed Wages and Incentive Effects: Statistical Evidence from Payroll Records. *International Economic Review*, 41(1), 59-92.

Pendleton, A., Whitfield, K., and Bryson, A. (2009). The Changing Use of Contingent Pay in the Modern British Workplace. In: Brown, W., Bryson, A., Forth, J., and Whitfield., K. (Eds.). *The Evolution of the Modern Workplace*. Cambridge: Cambridge University Press.

Peri, G., and Sparber, C. (2009). Task Specialization, Immigration, and Wages. *The American Economic Journal: Applied Economics*, 1(3), 135-169.

Peterson, N. G., Mumford, M. D., Borman, W. C., Jeanneret, P. R., and Fleishman, E. A. (1995). *Development of Prototype Occupational Information Network (O*NET) Content Model. Volume I: Report*. Salt Lake City: Utah Department of Workforce Services.

Prendergast, C. (2011). What Have We Learnt about Pay for Performance? Geary Lecture Winter 2010. *The Economic and Social Review*, 42(2), 113-134.

Rosen, S. (1978). Substitution and Division of Labour. *Economica*, 45(179), 235-250.

Shapiro, S. S., and Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, 52(3/4), 591-611.

Shearer, B. (2004). Piece Rates, Fixed Wages and Incentives: Evidence from a Field Experiment. *The Review of Economic Studies*, 71(2), 513-534.

Slichter, S. H., Healy, J. J. and Livernash, E. R. (1960). *The Impact of Collective Bargaining on Management*. Washington, D.C.: Brookings Institution Press.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics*, 24(2), 235-270.

U.S. Department of Labor (1991). *Dictionary of Occupational Titles*, 4th Edition. Washington, D.C.: U.S. Government Printing Office.

Warwick Institute for Employment Research (2017). Cascot: Computer Assisted Structured Coding Tool. Retrieved from: http://www2.warwick.ac.uk/fac/soc/ier/software/cascot/.

Wooldridge J. M. (2015). *Introductory Econometrics: A Modern Approach*, 6th Edition. Boston: Cengage Learning.

Appendix 1: Description and illustration of the data

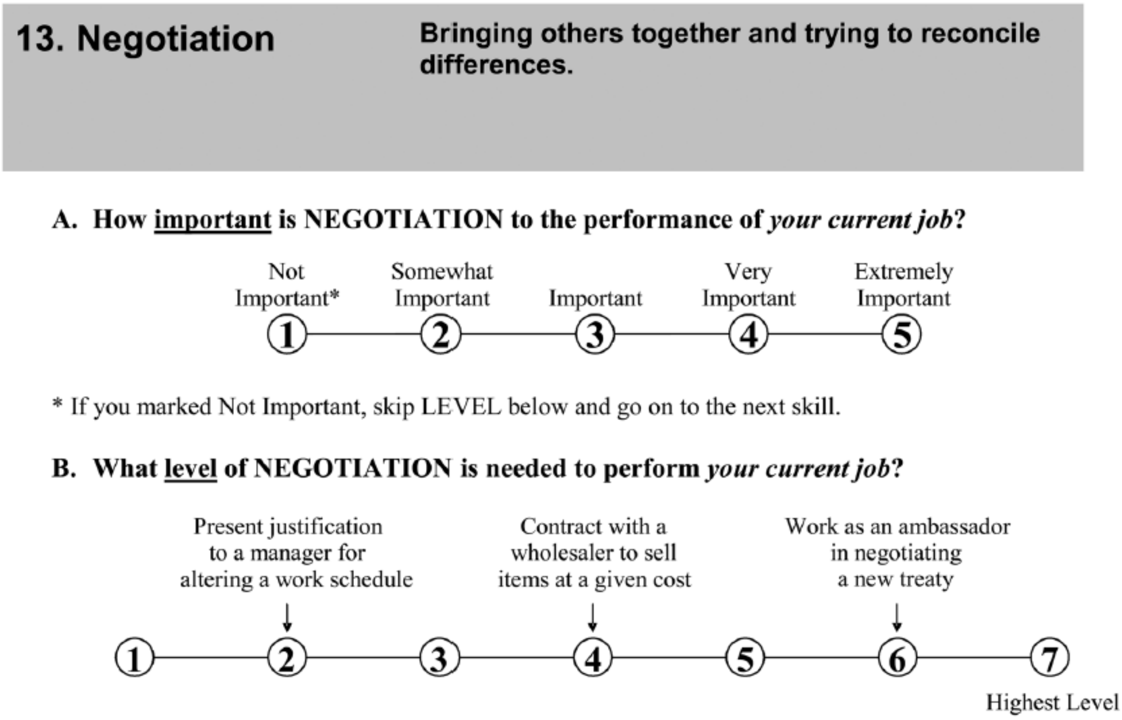
Table 6. Variables WERS data

Name	Description	Coding
payment by results	'Do any of the employees in this workplace get paid by results?' Definition payment by results: 'Payment by results' includes any method of payment where the pay is determined by the amount done or its value, rather than just the number of hours worked. It includes commission, and bonuses that are determined by individual, workplace or organisation productivity or performance. It does not include profit-related pay schemes.'	1: 'Payment by results' 0: otherwise
importance output quality	'To what extent would you say that the demand for your [main] product or service depends upon you offering better quality than your competitors?'	1: Demand does not depend at all on quality 5: Demand depends heavily on superior quality (Possible answers 1, 2, 3, 4, 5)
number competitors	'How many competitors do you have for your [main] product or service?'	1: None/Organisation dominates market 2: Few competitors 3: Many competitors
foreign owned	'Which of the following statements best describes the ownership of this workplace?'	1: 'Predominantly foreign owned' or 'Foreign owned/controlled' 0: otherwise
international market	'Is the market for your [main] product or service primarily ...'	1: Local 2: Regional 3: National 4: International
firm size	'Currently how many employees do you have on the payroll at this workplace?'	
proportion part time	Number of part-time employees / Number of employees	
proportion women	Number of women / Number of employees	
proportion union members	Number of union members / Number of employees	
meetings	'Do you have meetings between line managers or supervisors and all the workers for whom they are responsible?'	1: yes 0: no

region	Region in the UK	1: North (5.56%) 2: Yorkshire and Humberside (7.95%) 3: East Midlands (6.49%) 4: East Anglia (3.77%) 5: South East (32.65%) 6: South West (8.40%) 7: West Midlands (7.72%) 8: North West (11.68%) 9: Wales (5.49%) 10: Scotland (10.30%)
industry	SIC 2007 section	AB: Agriculture and Mining (0%) C: Manufacturing (8.73%) D: Electricity, gas, steam and air conditioning supply (1.94%) E: Water supply, sewarage and waste management (1.87%) F: Construction (3.84%) G: Wholesale and retail (10.67%) H: Transportation and storage (5.37%) I: Accommodation and food service (6.19%) J: Information and communication (2.46%) K: Financial and insurance activities (1.79%) L: Real estate activities (2.61%) M: Professional, Scientific and Technical Activities (5.45%) N: Administrative and Support Service Activities (4.25%) O: Public administration and defence (8.81%) P: Education (13.10%) Q: Human health and social work activities (15.75%) R: Arts, entertainment and recreation (4.03%) S: Other service activities (3.13%)

Figure 1: ONET questionnaire

The following graph shows an example how the questions are presented to the participant (Handel 2016).



13. Negotiation **Bringing others together and trying to reconcile differences.**

A. How <u>important</u> is NEGOTIATION to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
1	2	3	4	5

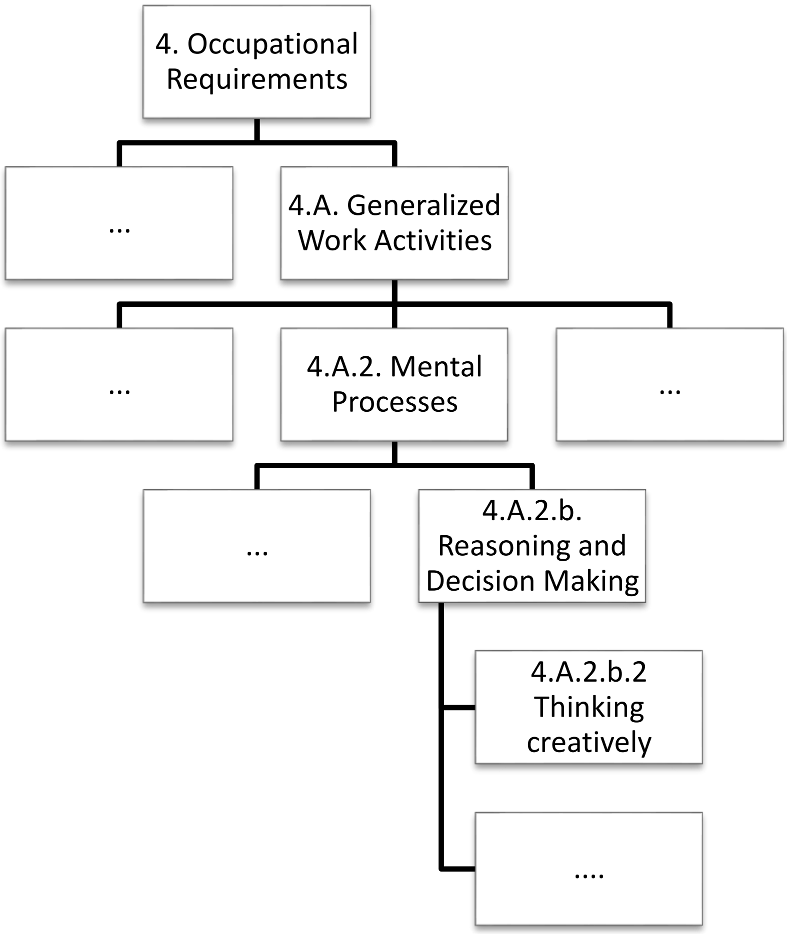
* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What <u>level</u> of NEGOTIATION is needed to perform *your current job*?

1	2	3	4	5	6	7
	Present justification to a manager for altering a work schedule		Contract with a wholesaler to sell items at a given cost		Work as an ambassador in negotiating a new treaty	Highest Level

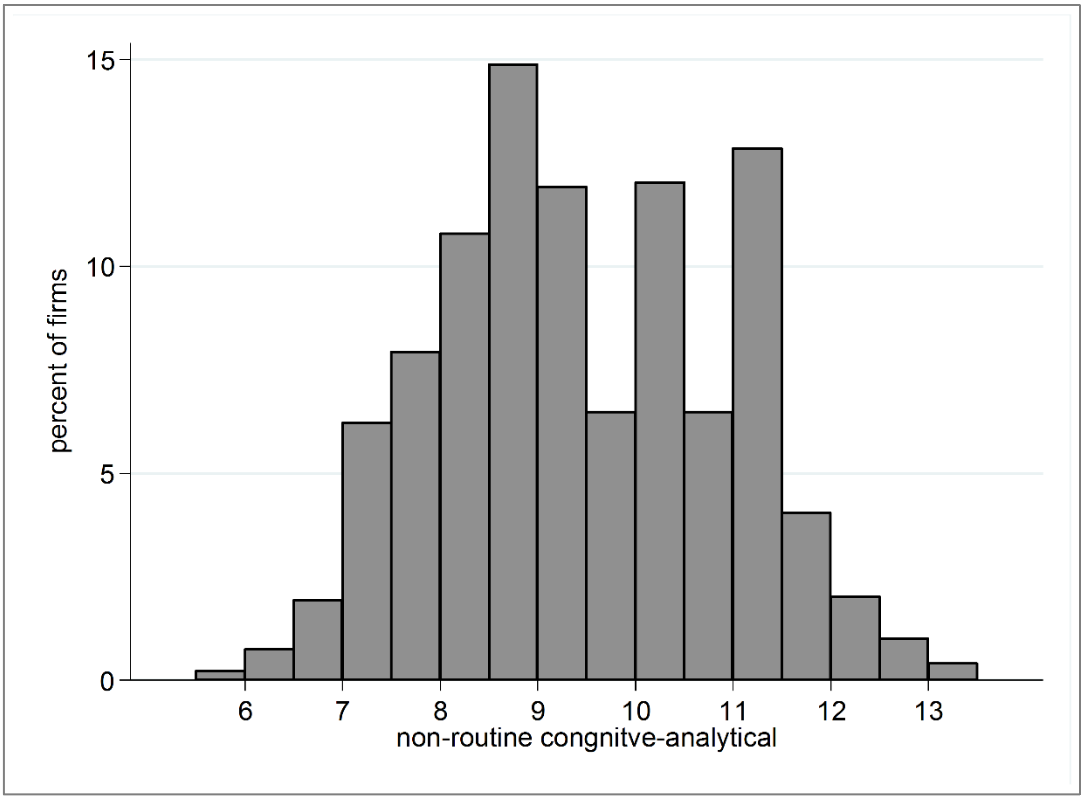
Figure 2: Hierarchy ONET

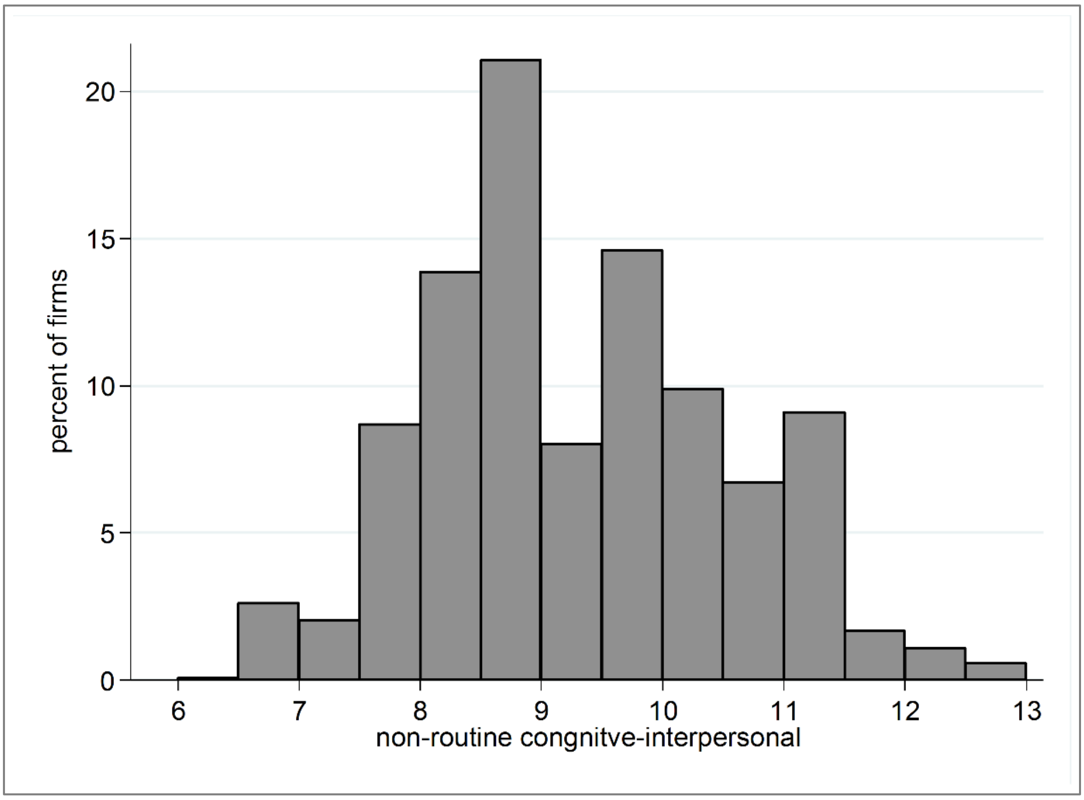
The following graph illustrates the hierarchy of the ONET descriptors using the example of 'Thinking Creatively (4.A.2.b.2).' Every descriptor has a code; each digit of the code contains information about one level in the hierarchy. The code gives detailed information about how the descriptor is classified within the ONET hierarchy (O*NET Resource Center 2017a).

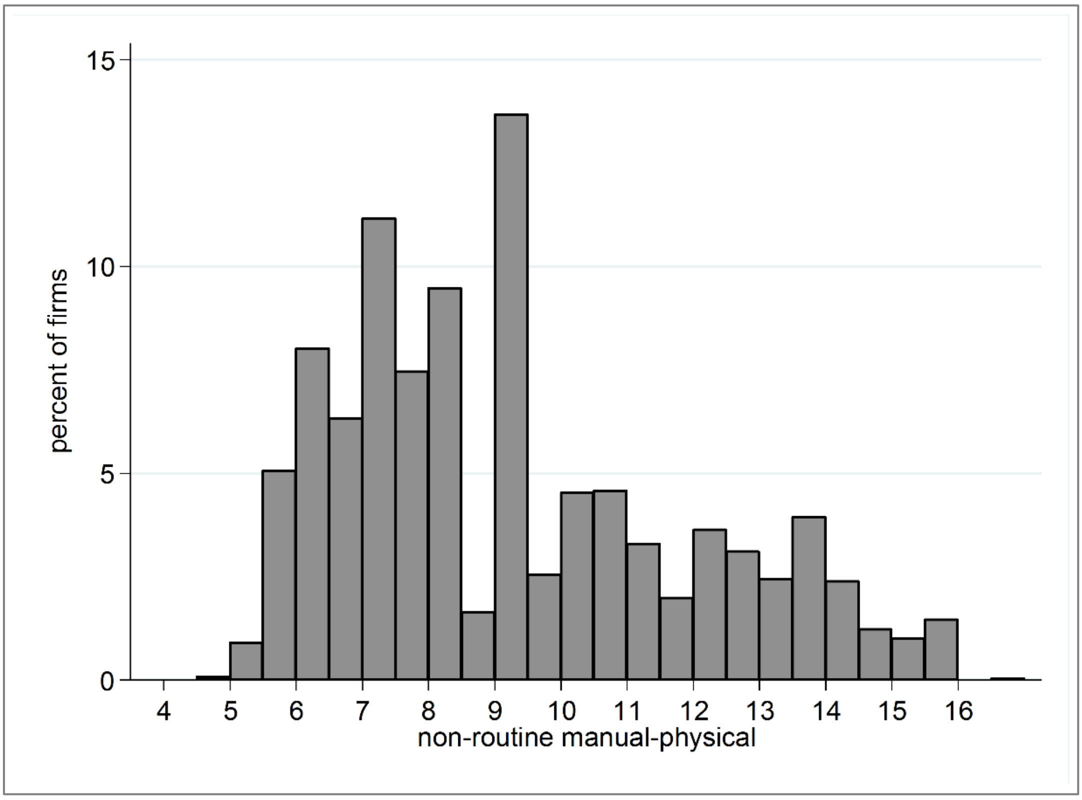


Figures 3-7: Histograms for the job content measures

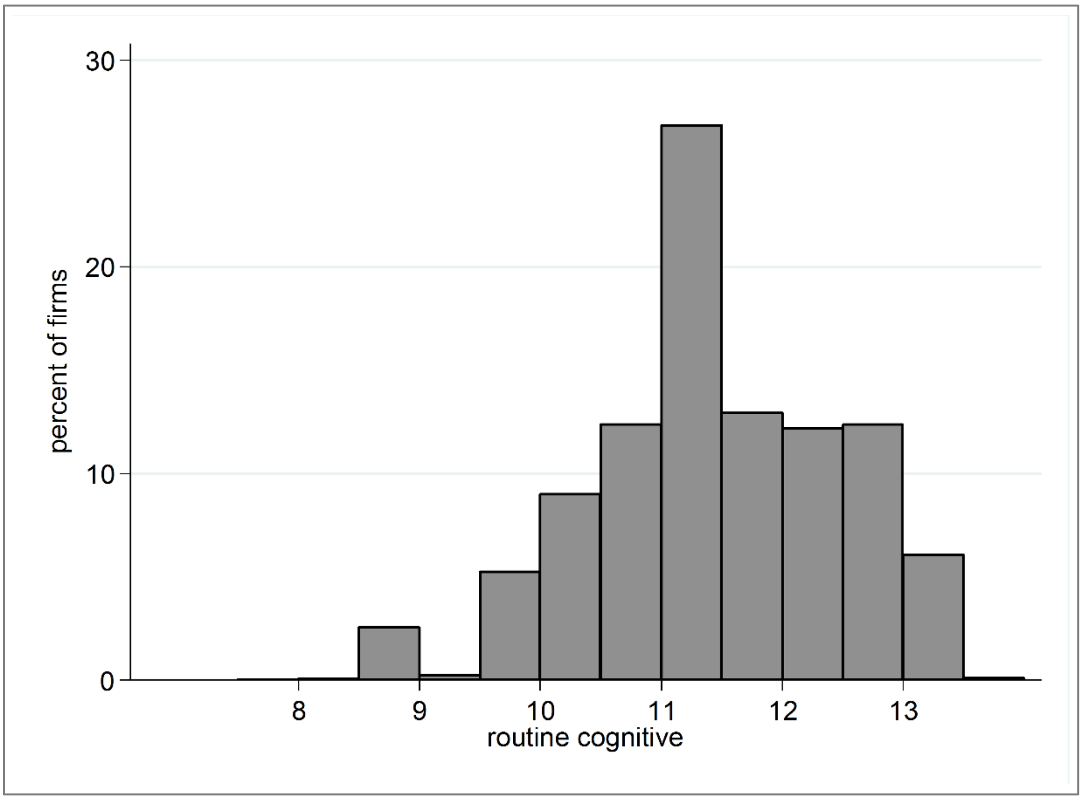
The histograms present the non-standardized values of the job content measures.







percent of firms
0
5
10
15
4
5
6
7
8
9
10
11
12
13
14
15
16
non-routine manual-physical



percent of firms
0
10
20
30
8
9
10
11
12
13
routine cognitive

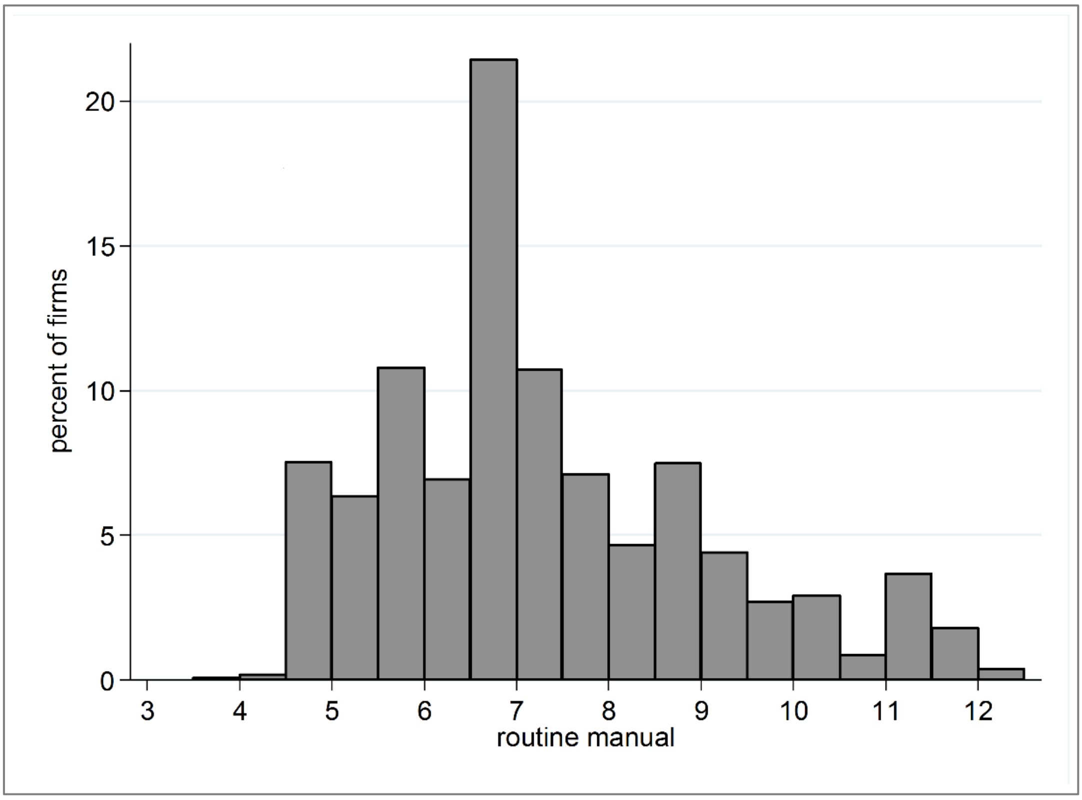

percent of firms
0
5
10
15
20
3
4
5
6
7
8
9
10
11
12
routine manual

Table 7. Correlation matrix: Pearson's r

	PBR	NRCA	NRCI	NRMP	RC	RM	quality	comp.	foreign	inter. market	frim size	part-time	women	union	meeting
PBR	1														
NRCA	0.07**	1													
NRCI	0.02	**0.64*****	1												
NRMP	-0.09***	-0.48***	-0.45***	1											
RC	0.07**	0.35***	0.15***	-0.38***	1										
RM	-0.04	**-0.58*****	**-0.52*****	**0.79*****	-0.25***	1									
quality	0.01	-0.04	0.01	-0.04	-0.06*	-0.002	1								
competitors	0.08***	-0.01	0.02	-0.04	-0.03	-0.01	0.14***	1							
foreign	0.11***	0.04	-0.08**	0.06*	0.04	0.08***	-0.01	-0.04	1						
inter. market	0.13***	0.15***	-0.10***	0.02	0.11***	0.13***	0.03	0.05*	0.28***	1					
firm size	0.05*	0.13***	0.06**	-0.07**	0.09***	-0.04	0.03	0.009	0.1***	0.23***	1				
part-time	-0.12***	-0.20***	0.15***	-0.18***	-0.12***	-0.16***	0.006	-0.01	-0.22***	-0.42***	-0.1***	1			
women	-0.08**	-0.005	0.22***	-0.45***	0.05*	-0.41***	0.06*	0.01	-0.23***	-0.35***	-0.09***	0.54***	1		
union	-0.04	0.03	-0.02	0.15***	0.02	0.09***	-0.1***	-0.15***	0.16***	0.11***	0.26***	-0.16***	-0.21***	1	
meeting	0.07**	0.06**	0.02	-0.08**	0.03	-0.06*	0.02	-0.05*	0.09***	0.17***	0.12***	-0.073**	-0.032	0.14***	1

Variables are abbreviated due to reasons of space: PBR: payment by results, NRCA: non-routine cognitive-analytical, NRCI: non-routine cognitive-interpersonal, NRMP: non-routine manual-physical, RC: routine cognitive, RM: routine manual. Correlations bigger than 0.5 among the main explanatory variables are highlighted. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.

Appendix 2: Regression diagnostics and robustness checks

Table 8. Regression results logit

	payment by result				
	(1)	(2)	(3)	(4)	(5)
non-routine cognitive-analytical	0.229** (0.086)	0.1 (0.093)	-0.035 (0.101)	-0.022 (0.102)	-0.073 (0.126)
non-routine cognitive-interpersonal	-0.135 (0.088)	-0.047 (0.091)	0.037 (0.095)	0.043 (0.096)	0.166 (0.113)
non-routine manual-physical	-0.340*** (0.1)	-0.286** (0.101)	-0.353*** (0.106)	-0.341** (0.107)	-0.178 (0.119)
routine cognitive	0.044 (0.072)	0.047 (0.073)	0.040 (0.074)	0.044 (0.074)	-0.042 (0.083)
routine manual	0.258* (0.103)	0.145 (0.107)	0.103 (0.109)	0.130 (0.110)	-0.022 (0.132)
controls I: operating environment		Yes	Yes	Yes	Yes
controls II: characteristics workforce			Yes	Yes	Yes
controls III: dummies region				Yes	Yes
controls IV: dummies industry					Yes
observations	1477	1477	1477	1477	1477

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. For clarity, the values of the single control variables are not presented. The identification strategy and the sets of control variables are identical with the baseline regression.

Table 9. Logit coefficients and average marginal effects for the full model

	payment by result	
	(1) logit coefficients	(2) average marginal effects
non-routine cognitive-analytical	-0.073 (0.126)	-0.14 (0.024)
non-routine cognitive-interpersonal	0.166 (0.113)	0.032 (0.216)
non-routine manual-physical	-0.178 (0.119)	-0.034 (0.23)
routine cognitive	-0.042 (0.083)	-0.008 (0.157)

routine manual	-0.022 (0.132)	-0.004 (0.025)
controls I: operating environment	Yes	Yes
controls II: characteristics workforce	Yes	Yes
controls III: dummies region	Yes	Yes
controls IV: dummies industry	Yes	Yes
observations	1477	1477

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. For clarity, the values of the single control variables are not presented. The identification strategy and the sets of control variables are identical with the baseline regression.

Table 10. Regression results OLS: Variance inflation factors, Shapiro-Wilk test, and Breusch-Pagan Test

	(1) payment by results OLS full model	(2) variance inflation factors
non-routine cognitive-analytical	-0.018 (0.024)	3.89
non-routine cognitive-interpersonal	0.032 (0.022)	2.71
non-routine manual-physical	-0.036 (0.023)	4.10
routine cognitive	-0.008 (0.016)	1.48
routine manual	-0.009 (0.025)	4.72
controls I, II, III, IV	Yes	Yes
observations	1477	1477
Shapiro-Wilk test (p-value)	0.000	
Breusch-Pagan Test (p-value)	0.000	

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. For clarity, the values of the single control variables are not presented. The identification strategy and the sets of control variables are identical with the baseline regression. The row labeled 'Shapiro-Wilk test' refers to the null hypothesis that the errors are normally distributed. The row labeled 'Breusch-Pagan Test' refers to the null hypothesis that the variance is constant.

Table 11. Regression results OLS: Alternative specification addressing collinearity concerns

	payment by result				
	(1)	(2)	(3)	(4)	(5)
non-routine cognitive-analytical	0.037*	0.013	-0.014	-0.013	-0.015
	(0.018)	(0.019)	(0.020)	(0.020)	(0.022)
non-routine cognitive-interpersonal	-0.036	-0.013	0.006	0.007	0.032
	(0.019)	(0.020)	(0.020)	(0.020)	(0.022)
non-routine manual-physical	-0.036*	-0.041**	-0.063***	-0.057**	-0.041*
	(0.015)	(0.015)	(0.017)	(0.017)	(0.018)
routine cognitive	0.016	0.013	0.010	0.012	-0.009
	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)
controls I: operating environment		Yes	Yes	Yes	Yes
controls II: characteristics workforce			Yes	Yes	Yes
controls III: dummies region				Yes	Yes
controls IV: dummies industry					Yes
observations	1477	1477	1477	1477	1477
R^2	0.01	0.04	0.06	0.07	0.14

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively. For clarity, the values of the single control variables are not presented. The identification strategy and the sets of control variables are identical with the baseline regression.

Table 12. Summary statistics reduced sample

Panel A	**Mean**	**S.d.**	**Min**	**Max**	**N**
payment by results	0.33	0.47	0	1	1477
importance output quality	4.14	0.97	1	5	1477
number competitors	2.56	0.57	1	3	1477
foreign owned	0.16	0.36	0	1	1477
international market	2.26	1.14	1	4	1477
firm size	244.9	881.0	5	11605	1477
proportion part time	0.27	0.29	0	1	1477
proportion women	0.48	0.28	0	1	1477
proportion union members	0.11	0.23	0	1	1477
meetings	0.78	0.41	0	1	1477
Panel B	**Mean**	**S.d.**	**Min**	**Max**	**N**
non-routine cognitive-analytical	9.13	1.40	5.76	13.20	1477
non-routine cognitive-interpersonal	9.09	1.06	6.44	12.85	1477
non-routine manual-physical	9.76	2.64	4.54	15.77	1477
routine cognitive	11.34	0.90	7.95	13.52	1477
routine manual	7.71	1.80	3.62	12.20	1477

Table 13. Regression results OLS: Compression reduced samples and full sample for the naïve model

	payment by result	
	(1)	(2)
	adjusted sample	full sample
non-routine cognitive-analytical	0.051**	0.052***
	(0.019)	(0.014)
non-routine cognitive-interpersonal	-0.031	-0.049***
	(0.019)	(0.013)
non-routine manual-physical	-0.072***	-0.069***
	(0.021)	(0.015)
routine cognitive	0.010	-0.002
	(0.016)	(0.009)
routine manual	0.054*	0.079***
	(0.022)	(0.017)
observations	1477	2669

Standard errors in parentheses. *, **, and *** denote significance at the 5%, 1%, and 0.1% levels, respectively.