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# Digital Control and Labor Flexibility: Are Firms Taking the Low Road?

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# Abstract

Historically, technological innovation has gone hand in hand with changes in the nature of work. During the industrial revolution the technology of mass production led to professions being reduced to assembly line work done by expendable workers. It is possible that present day digitalization is bringing about similar changes. This research focusses on the aspect of work tempo monitoring technology and whether usage of it by firms leads to more flexible labor relations. Differences of this effect between sectors are also examined. Building on theoretical concepts like lean management and the flexible firm this study argues that the use of this technology and the use of flexible contracts are compatible strategies. Drawing on data from the 2019 European Company Survey (ECS) this study analyses the strategies of firms in the Netherlands, Belgium and Germany by means of logistical regression. The results indicate no significant relationship between the degree of digital tempo monitoring and the proportion of flexible contracts, nor any statistically strong variation across sectors. However, firms in the construction sector show a slight positive trend, suggesting possible sector-specific effects that merit further investigation. These findings suggest that work tempo monitoring technology are not systematically linked to labor flexibilization. However, it is possible that this may be the case in the future, as few firms have yet adopted said technology. It is recommended that future research should focus on specific sectors or strictly on firms where technology which monitors work tempo is applied. As digital technologies continue to spread and evolve, ongoing research is necessary to monitor their long-term impact on employment relation and job quality across sectors.

# Contents

# Introduction

Since the Industrial Revolution, research has explored how technological innovation impacts the nature of work. One influential early theory that emerged with the rise of mass production lines was scientific management, or Taylorism (Edgell & Granter, 2020). This model emphasized the efficiency of a system where managers designed production processes to maximize labor productivity by subdividing tasks within the production line. As this approach gained traction, long-standing professions were increasingly broken down into bundles of discrete tasks, reshaping them into more fragmented jobs. The resulting transformation in the nature of work contributed to various forms of alienation experienced by workers. Taylorism also affected the kinds of skills workers developed, leading to the deskilling of labor. These jobs demanded fewer skills and competencies than the original professions, ultimately weakening workers' bargaining power. This raises the question whether new technological developments in the workplace are having a similar effect.

The present labor market is globalized and increasingly digitalized. The digitalization of work has thus far included computerization, automation and robotization of labor. All these aspects of digitalization have had an impact on the quality of work (Been & Huisman, 2023; Kirchner et al., 2023; Smids et al., 2020). Technological advancement is itself a leading cause of the globalization. International transport is improved and is made faster which allowed for more trade worldwide. Communication across the world is made more convenient via phones and the internet. This, in turn, has made the location where work is done increasingly irrelevant. This has allowed firms more options to outsource or offshore parts of their production process. Firms who have the means to do so are increasingly making use of those options (Standing, 2011). While this has led to more efficient production lines, lower costs, and consequently lower prices, this has had a downside; it has put workers across the globe in competition with each other.

The increased competition of employees across the globe has had a depressing effect on wages and other working conditions (Standing, 2011). This is not uniformly true for all types of work; for certain higher skilled jobs the technological innovations and globalization were beneficial. These would include jobs with specialized skills. For other workers in other jobs, whose skills were becoming increasingly replaceable these changes caused more insecurity (Doellgast et al., 2018). In the latter case long-term employment seems to make place for more flexible labor relationships as the gig economy emerges. This is another byproduct of digitalization as it has allowed work to be more short-term and mediated by platforms. These changes in the lower segments of the labor market have significant consequences for the lives of workers. Standing (2011) described how these global changes have eroded job and therefore income security, which is particularly a problem for people who rely on these jobs. This in combination with increased workplace surveillance and management by algorithms is reducing individual's sense of autonomy. This is a similar development to the alienation in the era of Taylorism. The present digital transformations of work may cause workers to experience a loss of control over the pace and structure of their work.

A substantial amount of research has been done on the causes and on consequences of labor market flexibilization (Dekker & Koster, 2017; Standing, 2011), including how firms use flexibility as a deliberate business strategy (Atkinson, 1984). More recent studies on firm's approaches to human resource management have been making a distinction of high road and low road strategies. The high road strategies involve investing in employees and their development and low road strategies prioritize cutting costs. Relatively little research has been done on how recent technological development and implementations of it has affected company strategy on human resource management. Specifically how digital innovation may influence firm's opting for high road or low road strategies. Koster, 2022 has found that digitalization gives firms the opportunity to opt for more low road strategies. In an attempt to link digital innovation to firms' human resource management strategies, this research paper attempts to find out whether this opportunity is utilized. It will hence attempt to answer the question:

*To what extent does the degree of work tempo monitoring through digital means relate to the use of flexible contracts by firms, and does this differ between sectors?*

# Theoretical Framework

Flexible labor refers to workers who are hired solely on temporary basis and so are not part of the core workforce. They include freelancers, workers with temporary contracts, zero hour contracts and those working via an employment agency. The degree in which companies hire flexible labor is part of what is known as numerical flexibility; the ability of the firm to adjust its labor quantity to meet fluctuations in demand. Digital means that determine the work tempo of workers can take many forms. The classical example from Taylorism is the assembly line, whose speed determines how fast the factory worker has to work on given tasks (Edgell & Granter, 2020). Contemporary examples include management by algorithms, for example forklift drivers, warehouse workers, administrative work; anything where a machine or computer decides what a worker does for how long.

When it comes to human resource management firms can take low road and high road strategies. High road strategies entail investing in employees by increasing benefits like wages and opportunities for skill development. Low road strategies entail increasing efficiency by cost cutting, often at the expense of the quality of jobs. Increasing the numerical flexibility of a firm can be interpreted as a low road strategy; the aforementioned ability adjust labor quantity is a means to cut costs when costs are not necessary. As demand for a good or service fluctuates it is more convenient for firms to not have to hold on to the manpower required to meet the peaks in demand, and it is more convenient to be able to take on more manpower with minimal commitments to the workers when that demand increases. This increases a firm's cost efficiency by having to pay less wages. In turn that does negatively affect job quality by reducing job security; the risks of commercial enterprise is transferred to the employees (Standing, 2011; Doellgast et al., 2018).

Regarding numerical flexibility it has been observed in transport and audiovisual sectors that firms have a lot of room for choice despite how insecure the business environment may be (Dekker & de Beer, 2015). Nonetheless, the question of to what degree a firm should hire workers on flexible contracts remains a result of a cost-benefit analysis (Dekker & Koster, 2017). On the one hand hiring through flexible contracts can minimize costs during periods of low customer demand, and it minimizes costs when it comes to secondary job benefits like paid sick leave and retirement contributions. On the other hand, when firms require employees with specific knowledge or skills essential to the core operations of the firm, the firms have an interest to keep these employees within the firm. Losing these hard to replace essential workers can increase the administrative costs and in case there is a shortage of them the firm may lose production capacity. This would incentivize firms to take a high road approach to these employees by offering a permanent contract and relatively generous employment benefits. Strategies like these have been observed in past research where more knowledge intensive jobs were less subject to low road strategies and flexibilization (Dekker & Koster, 2017; Koster, 2022). A combination of high road and low road approaches is possible by offering benefits to employees with flexible contracts (Dekker & de Beer, 2015; Dekker & Koster, 2017). However, the consideration of these hybrid approaches are beyond the scope of this research.

This attitude of firms to high road and low road strategies resemble the 'flexible firm' proposed by Atkinson (1984), in which he described observing firms having a core group of employees who enjoy the most employment benefits including job security, and multiple layers of increasingly flexible peripheral employment which the firm ideally scale up and down according to need. The jobs in the outer periphery are described to require non-firm-specific skills.

Modern business practices tend to be informed by the principles of lean management. These include continuous improvement of the production process by increasing efficiency and eliminating waste of resources including labor, (storage) space. Another one is 'just-in-time' production; this means that resources and labor are mobilized exactly when they are needed (Edgell & Granter, 2020). These principles seem compatible with Atkinson's idea of the flexible firm. The up and downscaling of the workforce can be a means to meet those principles; by being able to adjust the labor supply to market demand firms eliminate waste by wage costs. The concept of continuous improvement is also applied to the use of technology itself by continuous evaluation of the production process to make it more efficient; for example by automating parts of the process, and rearranging and reallocating tasks. This has been observed by Björkdahl (2020); pursuing greater operational efficiency tends to be the focus of firm's digitalization efforts instead of overall growth. Technology that optimizes the production process also includes that which exerts control over the pace of work itself; for example digital platforms which track time employees spend on tasks, management by algorithms and other types of workplace surveillance (Kayas, 2023). This opportunity to monitor the work of employees increases employer control of the production process to the detriment of the autonomy of employees. This allows companies to lower the standards of skills they have for employees, as the production process may depend less on human creativity (Smids et al., 2020). Employees who would possess these skills would, within the framework of the flexible firm, be moved from the core to the periphery.

Within the framework of lean management strategies it is thus reasonable to believe that flexibilization of the workforce and the degree in which digital means that determine the work tempo go hand in hand; business strategies that combine numerical flexibility and technology that monitors the labor process fit in lean management's principles to be adaptable to consumer demand and to be continuously optimized. This leads to the first hypothesis:

H1: *As companies make more use of digital means which monitor/determine the work tempo, the proportion of flexible contracts is higher within those companies.*

A sequential relation is presumed because of the scope of this research.

It has been observed that digitalization has had heterogenous effects on different jobs with regard to change in autonomy; Kirchner et al. (2023) found that in the service and manufacturing sectors digitalization decreased employee autonomy and in knowledge-based jobs autonomy increased. Jobs differ substantially in the nature of their production processes. That also determines to what extent tasks can be digitalized and potentially rearranged, as being part of an overall digitalization of the production process. Digital means that monitor or determine the work tempo of employees is a component of that. There is a limit to how much of the total production process management can get to control using these means. Therefore, the way that certain jobs will move to the flexible periphery within the wider strategy of (re)structuring the production process would differ for each sector as well. This leads to the second hypothesis.

H2: *The effect of digital means which monitor/determine the work tempo on the proportion of flexible contracts is different across sectors of establishments.*

**Control variables**

To gather insights on these hypotheses certain other effects on flexibilization need to be taken into account. Firstly, the country in which a given firm is established matters. Each country may have its own laws and regulations regarding employment and so will have varying levels of access to the digital means required to monitor employees, and varying ease in hiring flexible labor. Moreover, every country has its own distinct network of institutions in which the companies are embedded and each country has different relations between companies and said country's (governmental) institutions (DiMaggio & Powell, 1983). This national context forms the framework in which companies have to determine their strategy. Controlling for this variable takes out the different influences of institutional environments to the main effect. Another factor that has influence is the size of a given firm. It has been established that the choice of high road and low road strategies by firms is the result of weighing costs and benefits. It has been observed by Dekker & Koster (2017) that smaller companies opt for low road strategies because they tend to lack the means for choosing high road strategies in comparison to larger companies. Lastly, how quickly the need for certain knowledge and skills change for firms has implications for increasing or decreasing a firm's numerical flexibility. As in Atkinson's (1984) model makes a distinction of core employees who are essential for the company and a flexible layer employees in the periphery. Ideally employees whose skills and expertise are only needed temporarily are hired only for that period and no longer. This is why it is expected that the required knowledge and skills 'volatility' has an influence on the degree in which the companies in question opt for flexible hiring.
A conceptual model is given in figure 1.

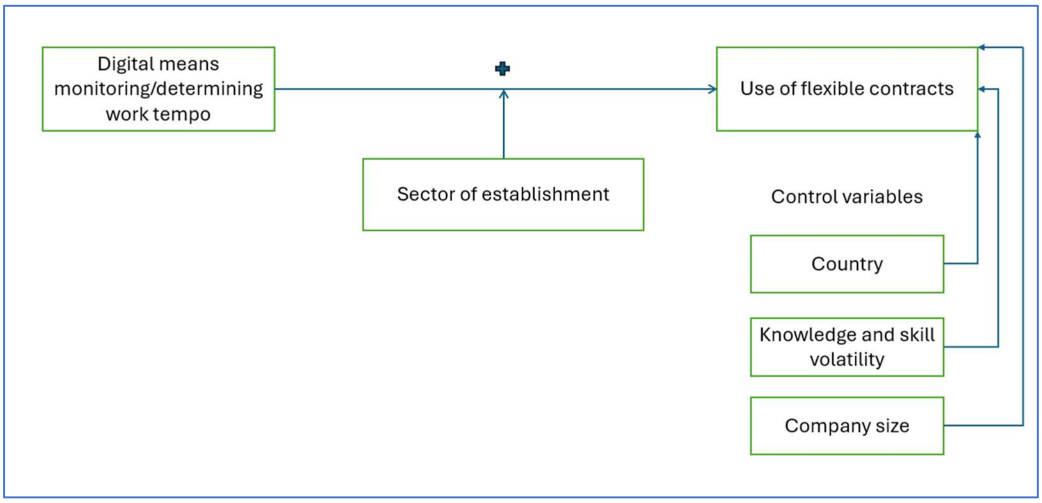


*Figure 1: The conceptual model*

# Methodology

**The Dataset**

To answer the research question The dataset that will be used to test the research hypotheses is the European Company Survey (ECS) carried out in 2019. The ECS is a cross-sectional survey that aims to map, assess and quantify information on company policies and practices across Europe and to monitor (European Company Surveys, n.d.). The survey is an initiative of European Foundation for the Improvement of Living and Working Conditions (Eurofound); a European Union (EU) agency who provides knowledge on how to plan and design better living and working conditions (Who we are, n.d.). The 2019 survey was carried out in collaboration with sister organization Cedefop which is focused at improving vocational education and training (Who we are, 2023).

The research population of the ECS comprises all companies within all 27 EU-member states and the United Kingdom (UK) with at least 10 employees or more. The survey consisted of an online questionnaire which had to be filled out by senior managers in charge of personnel of these companies and, where present, official employee representatives. The sampling was done as follows; the companies were contacted via telephone so these managers and possibly representatives could be identified. They were then contacted to complete the questionnaire online. Which companies to approach was chosen via multistage random sampling stratified by establishment or company size and then by the broad sector of activity (i.e. production, construction and services); Eurofound aimed for balancing a proportional representation of establishments per sector and the that of employees per sector.

In total 21.869 manager's interviews were completed and 3.073 employee representative interviews (ECS 2019 – Methodology, n.d). For this research only the manager's interview results will be used; there are more responses by managers than by employee representatives which means the results will be more generalizable.

Given scope limitations of this research the dataset will be filtered to only include firms in the following three countries; Netherlands, Belgium and Germany. The Netherlands is chosen because a large amount of the literature which is considered in the theoretical framework is research conducted in the Netherlands so hypotheses derived from said literature is most likely to be applicable there. Belgium and Germany are then chosen because they are neighboring countries with free trade and movement of people between them. They are also among the Netherlands' largest trading partners. Given the fact that their economies are so closely integrated but have separate laws and different institutions, they control well for the effect that is expected from a firm's country as described in the theoretical framework.

**Operationalization**

In this section the operationalization of the concepts in this research will be discussed. The coding, frequencies and recoding of these variables can be read in appendix 1.

*Digital means determining the work tempo*

The independent variable 'digital management determining the work tempo' is measured by a variable in the dataset which is the respondents answer to question 31 in the ECS-survey: *"For how many employees at this establishment is the pace of work determined by machines or computers? Your best estimate is good enough."* It has seven options: None at all, Less than 20%, 20% to 39%, 40% to 59%, 60% to 79%, 80% to 99% and All (coded as scores 1 to 7 respectively). This variable will be included in the analysis as a continuous variable.

*Use of flexible contracts*

The dependent variable 'use of flexible contracts' is constructed from a variable in the dataset which is the respondents answer to questions 14 in the ECS-survey: *"How many employees in this establishment have an open-ended contract? Your best estimate is good enough."* It has seven options: None at all, Less than 20%, 20% to 39%, 40% to 59%, 60% to 79%, 80% to 99% and All (coded as scores 1 to 7 respectively).

Originally this variable was going to be used in a linear regression analysis, but in an initial exploration of the data it has been established that such an analysis violated all the assumptions of linear regression. Hence, the hypotheses will instead be tested through logistic regression. The variable 'use of flexible contracts' is dichotomized for that purpose; categories 6 and 7 of the original variable will be coded as 0, and categories 1 to 5 will be coded as 1. The value 0 will mean that 80% to 100% of the employees of the firm are hired on open-ended contracts, which means that 0% to 20% are hired on flexible contracts. The value 1 will mean that 0% to 79% are hired on open-ended contracts, which means that more than 20% of employees are hired on flexible contracts. Flexible contracts are hence defined as any labor contracts which are not open-ended in this research. This dividing line is determined based on the data's skewness and the study's initial objective: to explain differences in the extent to which firms utilize flexible labor. Further details of the data exploration and other considerations which led to this decision is given in appendix 3.

*Sector of the establishment*

The moderator 'sector of the establishment' is a categorical variable. All companies were determined to be part of one of the following sectors before the survey was taken (the numbers denote the numerical scores of the categories); 1. Construction (NACE F), 2. Production (NACE B-E) and 3.

Services (NACE G-N, R and S). For the regression analysis this variable will be recoded as dummies; one for the construction sector and one for production sector. The service sector will be the reference category.

*Country*

The first control variable 'country' is a categorical variable. All firms were observed to be established in a certain country. This variable has 28 values; one for each EU-member state and candidate including the United Kingdom. Because the dataset will be filtered on the countries Netherlands, Belgium and Germany this variable can only take on the value for each of these three countries. For the regression analysis this variable will be recoded as dummies; one for Belgium and one for Germany. The Netherlands will be the reference category.

*Knowledge and skill volatility*

The second control variable 'knowledge and skill volatility' is a categorical variable which is the respondent's answer to question 33 in the ECS-survey: *"How quickly do the knowledge and skills needed from the employees in this establishment change?"* with the added note; *"If this differs a lot between different groups of employees, please think of the largest group of employees in this establishment."* It has four options: 'No change at all', 'Not very quickly', 'Fairly quickly' and 'Very quickly'. For the regression analysis this variable will be recoded as dummies; 'No change at all' will be the reference category and a dummy will be made for each of the other categories.

*Company size*

The third control variable 'company size' is a categorical variable. During the first phase of stratification for the stratified random sampling method Eurofound used, companies were picked by number of employees. All were determined to be in one of the following categories; '10 to 49 employees', '50 to 249 employees' and '250 employees or more'. For the regression analysis this variable will be recoded as dummies; '10 to 49 employees' will be the reference category and a dummy will be made for each of the other categories.

## Plan of analysis

The hypotheses have been tested by means of logistic regression; 'digital means determining the work tempo' was used as the independent variable and 'use of flexible contracts' as the dependent variable. The first hypothesis "*As companies make more use of digital means which monitor/determine the work tempo, the proportion of flexible contracts is higher within those companies."* is tested by examining the regression coefficients of 'digital management determining the work tempo'. The second hypothesis "*The effect of digital means which monitor/determine the work tempo on the proportion of flexible contracts is different across sectors of establishments."* is tested by examining the difference of regression coefficients of 'digital management determining the work tempo' between sectors.

Before the logistic regression analysis the univariate distributions of the variables were studied to get a preliminary impression of the data. Afterwards bivariate statistics were examined to see how all variables relate to each other. Following the descriptive statistics the logistic regression model is estimated. The continuous variable 'digital means determining the work tempo' has been centered beforehand. The resulting variable has been multiplied with the dummies constructed from the moderator variable 'sector of the establishment'. Four regression models have been estimated: The first model predicts 'use of flexible contracts' with the three control variables as predictors 'Country', 'Knowledge and skill volatility', 'Company size'. The second model predicts 'use of flexible contracts' using the same predictors as the first model and the added 'Digital management determining work tempo' variable. The third model builds upon that by adding the dummies of the 'Sector of establishment' variable as predictor. In the fourth model the interaction terms have been added. For each model the regression coefficients have been reported along with their standard errors, odds-ratio's and their p-values resulting from the coefficients' Wald-tests. The following modelfit-statistics will be given for each model as well; the deviance, their likelihood ratio tests and resulting p-values. For the fourth model the VIF-scores of the variables are also given. All these statistics are given in table 6. Before the analysis begins the assumption of logistic regression is addressed.

Analyzing the results started with evaluating the model fit. This has been done sequentially per model starting with model 1. For each model the results of the likelihood ratio tests and Hosmer-Lemeshow tests have been discussed. After that the influential points are discussed. The research hypotheses have been tested as follows: formulae to estimate probabilities were derived from table 6, then these formulae were used to estimate probability differences for different values of variables. After conclusions on the hypotheses were drawn the control variables are briefly discussed and multicollinearity is addressed by examining the VIF-scores of model 4.

# Results

The data of the 2019 ECS have been analyzed using software R. The computations of statistics discussed in this chapter are given in appendices 1 and 2. Of the original 2752 observations in the Netherlands, Belgium and Germany 2687 are left after removing the cases with missing values for at least one of the variables. This means there was minimal corruption by missing values.

## Univariate statistics

In this section the univariate distributions of the variables are discussed. The univariate statistics of all variables in the model are shown in table 1. The average score of the variable 'digital means determining work tempo' is 2.22. This means that for the average firm in the research sample for between 1% and 20% of the employees the pace of work is determined by machines or computers. The quartiles show the values which cut the distribution into four groups of equal size having arranged the sample in a sequence of ascending values. Looking at these, one can see that the second quartile, also known as the median, is equal to the minimum score of 1. This means that at least half of the sample has the lowest possible score, implying that at least half of the firms in the sample none of their employees have their work tempo determined by machines or computers. The third quartile is 3; this means that at most 25% of the firms in the sample more than 20% of their employees have their work tempo determined by machines or computers. Therefore within the sample the use of these technologies is not very widespread. Statistically this also means that the distribution is heavily right-skewed. This means that at least half of the firms in in the sample do not use work tempo monitoring technology at all.

Firms who have less than 20% of their employees hired through flexible contracts are in the vast majority (74.2%). That means that about three in four firms fall in this category. About one in four firms have 20% or more of their employees hired through flexible contracts (25.8%). This may pose problems for the logistic regression model as a heavily skewed outcome variable makes estimations of effects unreliable. Around two in three firms in the sample (64.6%) are part of the services sector, around a quarter (24.6%) are part of the production sector and around one in ten (10.8%) are part of the construction sector. This means that services is overrepresented in comparison to the other sectors. This is not very surprising considering it is a very broad category, ranging from financial and administrative sectors to education and entertainment sectors.

The three countries considered in this research are somewhat equally represented; 38.0% of the firms in the sample are situated in the Netherlands, 36.0% in Belgium and 25.6% in Germany. Germany is slightly underrepresented. The knowledge and skills which are required of employees seem to change throughout time for the vast majority of firms. Only 3.4% of the sample of firms report that they do not change at all. For more than half (63.5%) it seems to change but not very quickly. For 30.7% of firms they change fairly quickly. For very few firms (2.3%) they change very quickly. For the planned regression analysis this may mean that for the highest and lowest category of this variable the estimate of the dependent variable 'use of flexible contracts' may be unreliable. More than half of the firms in the sample are small in size; 58.0% of them report to comprise 10 to 49 employees. 30.0% of firms comprise 50 to 249 employees and 12.1% comprise more than 250 employees. Large firms are in a significant relative minority which thus also may lead to reliability issues for estimates in the regression analysis.

*Table 1: Univariate statistics for the dataset.*

| Variable | Category | M (SD)[a] | Min. | Q1 | Q2 | Q3 | Max. | N |
|---|---|---|---|---|---|---|---|---|
| Digital management determining work tempo | | 2.22 (1.66) | 1.00 | 1.00 | 1.00 | 3.00 | 7.00 | 2687 |
| Use of flexible contracts (in proportion of employees) | Less than 20%<br>20% or more | 74.2%<br>25.8% | | | | | | 2687 |
| Sector of establishment | Construction<br>Production<br>Services | 10.8%<br>24.6%<br>64.6% | | | | | | 2687 |
| Country | Netherlands<br>Belgium<br>Germany | 38.0%<br>36.4%<br>25.6% | | | | | | 2687 |
| Knowledge and skill volatility | No change<br>Not very quickly<br>Fairly quickly<br>Very quickly | 3.4%<br>63.5%<br>30.7%<br>2.3% | | | | | | 2687 |
| Company size (in number of employees) | 10-49<br>50-249<br>250 or more | 58.0%<br>30.0%<br>12.1% | | | | | | 2687 |

[a] for categorical variables the distribution is summarized in proportions.

## Bivariate statistics

In this section the relationships between variables will be discussed using association measures suitable to the different pairs of variables.

The relationship between the two main variables of the model 'digital means determining work tempo' and 'use of flexible contracts' is evaluated by comparing the conditional means of 'digital means determining work tempo' to the two different outcome groups of 'use of flexible contracts'. The result is given in table 2. There is no significant difference between of the mean value of 'digital means determining work tempo' for firms of which less than 20% of employees have flexible contracts and that for firms of which 20% or more have flexible contracts ($t$ = -0.36, $p$ = 0.72). For firms with a low degree of flexible contracts the mean is 2.23 and for firms with a high degree of flexible contracts it's 2.20. For both types of firms the average firm would use digital means that determine the work tempo for less than 20% of employees. This insignificant difference may indicate that the two main variables of the model are not related.

The relationship between the categorical variables, which are the moderator variable 'sector of the establishment' and the three control variables 'country', 'knowledge and skill volatility' and 'company size', are measured with the Cramer's V statistic. This statistic tells us to what degree two categorical variables are interdependent; how much is categorization along one spectrum related to categorization along another. Relationships between the categorical variables with 'digital means determining work tempo' are measured with multiple correlation coefficients; it reflects the strength of the relationship between groupings and outcome scores. The higher these scores, the stronger the relationship between the variables. Unlike correlation coefficients these statistics are directionless, meaning that the scores don't tell whether variables are positively or negatively related. These statistics are given in table 3.

The variable 'digital means determining work tempo' has a weak multiple correlation with 'sector of the establishment' ($R$ = 0.11; $p$ < 0.01) and a weak to moderate multiple correlation with 'company size' ($R$ = 0.15; $p$ < 0.01). That means there is a slight difference in use of digital means determining the work tempo of employees between firms in different sectors and of different sizes. There is a significant but negligible relation to the country the firm is established in ($R$ = 0.07; $p$ < 0.01). The 'use of flexible contracts' reports two weak relations; one to 'sector of establishment' ($V$ = 0.14; $p$ < 0.01) and one to 'company size' ($V$ = 0.11; $p$ < 0.01). The largest observed association metric is the Cramer's V between the 'use of flexible contracts' and the 'country' variable ($V$ = 0.32; $p$ < 0.01). This is a strong relation; this means that at least one of the countries has a large difference in amount of firms with a relatively highly or lowly flexibilized workforce. The variable 'knowledge and skill volatility' does not seem to be related to any of the other variables in the model only slightly with the variable ‘country’ ($V = 0.08$; $p < 0.01$). This means that the speed in which the knowledge and skills required from employees by companies do not differ much across different types of companies with the categorizations within this research. The variable ‘sector of establishment’ reports a weak relation to ‘country’ ($V = 0.09$; $p < 0.01$) and a moderate relation to ‘company size’ ($V = 0.19$; $p < 0.01$). The latter observation implies that some sectors may be comprised of larger firms than others. Lastly, ‘company size’ seems to be weakly to moderately related to ‘country’ ($V = 0.16$; $p < 0.01$), implying that the size of firms may differ across the three countries in the dataset.

Overall, the association metrics do not indicate problematic multicollinearity with the main predictor of the model ‘digital means determining work tempo’. The strong relationship between the dependent variable ‘use of flexible contracts’ with ‘country’ may imply that it is a better predictor than the main predictor, given the insignificant difference of means observed in table 2.

*Table 2: Mean comparison of digital means determining work tempo for the two outcome groups. (N = 2687)*

| | Use of flexible contracts | Mean | Mean difference | Two sided t-statistic | p-value |
|---|---|---|---|---|---|
| Digital means determining work tempo | Less than 20%<br>20% or more | 2.23<br>2.20 | -0.03 | -0.36 | 0.72 |

*Table 3: Association measures between variables (N=2687)*

| Variabele | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1.Digital means determining work tempo | - | | | | | |
| 2. Use of flexible contracts | X | - | | | | |
| 3. Sector of establishment | 0.11* | V=0.14* | - | | | |
| 4. Country | 0.07* | V=0.32* | V=0.09* | - | | |
| 5. Knowledge and skill volatility | 0.04 | V=0.01 | V=0.05 | V=0.08* | - | |
| 6. Company size | 0.15* | V=0.11* | V=0.19* | V=0.16* | V=0.05 | - |

*p<0.01; ANOVA F-tests for categorical x continuous variables; chi-squared tests for categorical x categorical variables.

## Assumptions

For the results of logistic regression to be valid the observations must be independent from one another. That means that the observation of one firm may not be dependent on the observation of another firm. The ECS selected a stratified random sample, wherein first was made sure that the sizes of firms and sectors were represented in proportions resembling European economy. When there was non-response from a firm they would approach another with the same characteristics. This means there may be some bias in that regard. Overall the firms were selected randomly within their strata. This assumption has been sufficiently met.

## Model evaluation

To test the quality of the logistical regression models two test statistics need to be considered; the likelihood ratio test and the Hosmer-Lemeshow test. The likelihood ratio test compares the deviance statistics between two models. The deviance is a metric for how much a model's predictions deviate from a hypothetical model which has a variable for each observation, and as such would make perfect predictions. A higher deviance thus indicates a poorer fit to the data. The likelihood ratio test thus tests how much the model's fit improves by adding predictors. The Hosmer-Lemeshow test is used to test whether the model's predictions are accurate; the test statistic is calculated by dividing the data into subgroups and test whether the model's predictions correspond with the observed values of the outcome variable. The lower the test statistic the better the more accurate the predictions are. Both test statistics are compared to a chi-squared distribution to determine statistical significance. For the likelihood ratio test a significant result indicates an improvement of fit and for the Hosmer-Lemeshow test a non-significant result indicates an improvement of fit.

The results of the model inspection can be seen in table 6. The deviance of the first model is 2789.6 and the likelihood-ratio test gives a significant result ($\chi^2(7)$ = 280.26; $p$ < 0.001). This means that the total of control variables improve the fit of the model; at least one of the added variables has a non-zero effect on the probabilities of the outcome variable. The Hosmer-Lemeshow test is not significant ($\chi^2(8)$ = 12.780; $p$ = 0.078), which means that the values predicted by the first model do not differ significantly from the observed values. The inclusion of the main predictor 'digital means determining work tempo' improves with regard to the deviance ($\chi^2(1)$ = 7.52; $p$ = 0.006), which means that this predictor improves the predicting power of the model. This model reports the lowest difference between predicted values and observed values as shown by the Hosmer-Lemeshow test ($\chi^2(8)$ = 12.508; $p$ = 0.130). The third model where the moderator categories of 'sector of the establishment' are added, improves significantly on the deviance as well ($\chi^2(2)$ = 54.00; $p$ < 0.001). There is indication that this model makes worse predictions overall however; the Hosmer-Lemeshow test reports a significant difference between the predicted and observed outcome values, the largest one yet ($\chi^2(8)$ = 25.798; $p$ = 0.002). These two test statistics may indicate that the sector of the firm is a good predictor for whether a firm has a low or high proportion of flexible employees, but that the rest of the variables do not make good predictions when sector is controlled for. The last model does not significantly improve on deviance well ($\chi^2(2)$ = 1.52; $p$ = 0.467) nor on making good predictions overall ($\chi^2(8)$ = 25.644; $p$ = 0.002). Hence, the interaction variables may not improve the model.

Considering the effect of 'digital means determining the work tempo' is no longer significant after the moderator variable 'sector of establishment' is added (see model 3), considering that the second model has a non-significant result on the Hosmer-Lemeshow test and the third and fourth model do not, and considering that the fourth (complete) model needs to be used to test the second research hypothesis, the accuracy of model 2 will be closer examined and compared with that of model 4 by means of classification tables. Table 4 is the classification table of model 2 and table 5 is the classification table of model 4. The complete model makes more accurate predictions in total; it predicts 76.4% of the data correctly compared to model 2's accuracy of 74.7%. Both models perform poorly in accurately predict which firms have a high proportion of flexible employees but the complete model more than doubles the accuracy compared to model 2; model 2 predicting 9.4% of them correctly and model 4 predicting 22.0% of them correctly. Model 2 outperforms the complete model in predicting which firms have a low proportion of flexible contracts by a negligible margin (97.4% against 95.3%, respectively). This means that the inclusion of the variable 'sector of establishment' definitely increases the quality of the model. The relatively good result of the Hosmer-Lemeshow test of model 2 can hence be disregarded. The overall accuracy of the complete model does not substantially improve on the empty model, which would be 74.2%. This is partially because of the skewed distribution of 'use of flexible contracts', but it is also an indication that the model does not fit the data.

*Table 4: Classification table of model 2 (N = 2687)*

| | | Predicted<br>Use of flexible contracts | | |
|---|---|---|---|---|
| Observed | | 0 | 1 | Percentage correct |
| Use of flexible | 0 | 1942 | 51 | 97.4% |
| contracts | 1 | 629 | 65 | 9.4% |
| Total percentage | | | | 74.7% |

*Table 5: Classification table of model 4 (N = 2687)*

| | | Predicted<br>Use of flexible contracts | | |
|---|---|---|---|---|
| Observed | | 0 | 1 | Percentage correct |
| Use of flexible | 0 | 1900 | 93 | 95.3% |
| contracts | 1 | 541 | 153 | 22.0% |
| Total percentage | | | | 76.4% |

## Influential points

The logistic regression model has been evaluated for influential points which may have a disproportionately large effect on the models estimations. For logistic regression the main metric which can be used for this is the leverage statistic. This statistic reflects the extent to which a given data point, in this case a firm, deviates from the overall pattern of values across the independent variables. The higher the leverage value the more a given firm has influence on the overall observed effects. To determine which leverage values are too high they have been tested against a threshold. The used threshold is the amount of variables in the model ($k$ = 12) multiplied by three, and then divided by the amount of data points ($N$ = 2687). Hence, a leverage value is considered to high if it exceeds *threshold* = 0.013. This led to 120 cases in the dataset to have high leverages. After re-estimating the complete model without these 120 cases, the difference of estimates was minimal for the main variables in the model. The slope of 'digital means determining the work sector' did not change significantly. Two noteworthy changes occurred; the slopes of for the variable 'knowledge and skill volatility' changed. The slopes of the dummies 'not very quickly' and 'fairly quickly' became positive instead of negative. Also the interaction term for the 'construction' sector quadrupled in effect size. Nonetheless all those slopes remained insignificant. It has been decided that the cases with high leverage will not be excluded from the analysis for that reason, and because of the fact that they are legitimately measured data points. They are not mistakes in measurement and thus they are worth including in the analysis.

*Table 6: Regression analysis explaining the use of flexible contracts by organizations (N = 2687)*

| | | 1 | | 2 | | 3 | | 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *b* <br> *(SE)* | *OR* <br> *(P)* | *b* <br> *(SE)* | *OR* <br> *(P)* | *b* <br> *(SE)* | *OR* <br> *(P)* | *b* <br> *(SE)* | *OR* <br> *(P)* | *VIF* |
| Intercept | | -0.125 | 0.883 | -0.141 | 0.869 | 0.044 | 1.045 | 0.036 | 1.037 | |
| | | (0.261) | (0.633) | (0.260) | (0.589) | (0.264) | (0.867) | (0.265) | (0.892) | |
| Country | *Netherlands* | | ref | | ref | | ref | | ref | |
| | *Belgium* | -1.602 | 0.202 | -1.620 | 0.198 | -1.596 | 0.203 | -1.600 | 0.202 | 1.153 |
| | | (0.117) | (<0.001) | (0.118) | (<0.001) | (0.118) | (<0.001) | (0.119) | (<0.001) | |
| | *Germany* | -1.240 | 0.289 | -1.289 | 0.275 | -1.232 | 0.292 | -1.229 | 0.293 | 1.141 |
| | | (0.118) | (<0.001) | (0.120) | (<0.001) | (0.121) | (<0.001) | (0.121) | (<0.001) | |
| Knowledge and skill | *No change at all* | | ref | | ref | | ref | | ref | |
| volatility | *Not very quickly* | -0.309 | 0.735 | -0.298 | 0.742 | -0.304 | 0.738 | -0.300 | 0.741 | 7.174 |
| | | (0.260) | (0.236) | (0.260) | (0.251) | (0.263) | (0.247) | (0.263) | (0.254) | |
| | *Fairly quickly* | -0.178 | 0.837 | -0.156 | 0.856 | -0.213 | 0.808 | -0.206 | 0.814 | 6.962 |
| | | (0.267) | (0.504) | (0.267) | (0.559) | (0.270) | (0.430) | (0.270) | (0.447) | |
| | *Very quickly* | -0.306 | 0.736 | -0.279 | 0.757 | -0.417 | 0.659 | -0.410 | 0.663 | 1.621 |
| | | (0.403) | (0.447) | (0.404) | (0.490) | (0.407) | (0.305) | (0.408) | (0.314) | |
| Company size | *10-49 employees* | | ref | | ref | | ref | | ref | |
| | *50-249 employees* | 0.142 | 1.153 | 0.180 | 1.198 | 0.305 | 1.356 | 0.300 | 1.350 | 1.156 |
| | | (0.105) | (0.176) | (0.106) | (0.089) | (0.108) | (0.005) | (0.109) | (0.006) | |
| | *250+ employees* | 0.447 | 1.563 | 0.497 | 1.644 | 0.688 | 1.990 | 0.686 | 1.987 | 1.206 |
| | | (0.139) | (0.001) | (0.141) | (<0.001) | (0.147) | (<0.001) | (0.147) | (<0.001) | |
| Digital means determining work tempo | | - | - | -0.080 | 0.923 | -0.028 | 0.972 | -0.050 | 0.951 | 1.556 |
| | | | | (0.030) | (0.007) | (0.031) | (0.357) | (0.036) | (0.163) | |
| Sector of establishment | *Service* | | ref | | ref | | ref | | ref | |
| | *Construction* | - | - | - | - | -0.599 | 0.550 | -0.556 | 0.573 | 1.107 |
| | | | | | | (0.173) | (<0.001) | (0.180) | (0.002) | |
| | *Production* | - | - | - | - | -0.859 | 0.424 | -0.906 | 0.404 | 1.433 |
| | | | | | | (0.130) | (<0.001) | (0.142) | (<0.001) | |
| Digital means determining | *Service* | | ref | | ref | | ref | | ref | |
| work tempo * Sector of | *Construction* | - | - | - | - | - | - | 0.112 | 1.118 | 1.158 |
| | | | | | | | | (0.132) | (0.398) | |
| establishment | *Production* | - | - | - | - | - | - | 0.075 | 1.078 | 1.710 |
| | | | | | | | | (0.075) | (0.313) | |
| *Deviance* | | | 2789.6 | | 2782.1 | | 2728.1 | | 2726.6 | |
| *LR-test (p)* | | | 280.26 (<0.001) | | 7.52 (0.006) | 54.00 | (<0.001) | | 1.52 (0.467) | |
| *HL-test (p)* | | | 12.780 (0.078) | | 12.508 (0.130) | 25.798 | (0.002) | | 25.644 (0.002) | |
| *N* | | | 2687 | | 2687 | | 2687 | | 2687 | |

*Note.* The reference category is a firm in the Netherlands with 10-49 employees of which the required skills do not change very quickly. For models 3 and 4 the additional reference category is the service sector.

## Hypothesis testing

In this paragraph the hypotheses are tested to the results of the logistic regression analysis. This was done by first examining models 2, 3 and 4 in table 6, in which the slopes, odds ratios, their standard errors and p-values of the Wald tests are given. The reference firm for table 6 is a firm in the Netherlands with 10-49 employees of which the required skills do not change, in the services sector. This reference group has been chosen because the Netherlands and the service sectors are the mode values of their respective variables. The rest of the variables have ordinal scales so the lowest ranking group is chosen for these variables to make the table more intuitive. As the slopes themselves cannot be intuitively interpreted on their own, the effects are evaluated by deriving the estimated probabilities from the models. The estimated probabilities are then presented in tables 7, 8 and 9. For these probability estimations the reference category for 'knowledge and skill volatility' has been changed to firms of which the knowledge and skills required by employees do not change very quickly. This way each variable's reference category corresponds with their mode.

**The formulae**

The probabilities in tables 7, 8 and 9 are calculated using the following formulae derived from the logistic regression table.

Formula model 2:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = -0.14 - 0.08x_{worktempo} - 1.62d_{Bel} - 1.29d_{Ger} - 0.30d_{vol1} - 0.16d_{vol2} - 0.28d_{vol3} + 0.18d_{size1} + 0.50d_{size2}$$

Formula model 3:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = 0.04 - 0.03x_{worktempo} - 1.60d_{Bel} - 1.23d_{Ger} - 0.30d_{vol1} - 0.21d_{vol2} - 0.42d_{vol3} + 0.31d_{size} + 0.69d_{size2} - 0.60d_{constr} - 0.86d_{prod}$$

Formula model 4:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = 0.04 - 0.05x_{worktempo} - 1.60d_{Bel} - 1.23d_{Ger} - 0.30d_{vol1} - 0.21d_{vol2} - 0.41d_{vol3} + 0.30d_{size} + 0.69d_{size2} - 0.56d_{constr} - 0.91d_{prod} + 0.11d_{constr} * x_{worktempo} + 0.08d_{prod} * x_{worktempo}$$

For all these formulae $x_{worktempo}$ is the variable 'digital means determining the work tempo', and $d_{Bel}$ and $d_{Ger}$ are the dummy variables for the countries Belgium and Germany respectively. The dummies

$d_{vol1}$, $d_{vol2}$ and $d_{vol3}$ are the dummies for the 'knowledge and skill volatility' variable; for the categories 'not very quickly', 'fairly quickly' and 'very quickly' respectively. The dummies $d_{size1}$ and $d_{size2}$ are the dummies for firms with between 50 and 249 employees and for firms with 250 or more employees respectively. Lastly the dummies $d_{constr}$ and $d_{prod}$ are those of the categories 'construction sector' and 'production sector. The parameter p denotes the probability and the caret accent above it indicates that it is an estimation.

**Estimation of probabilities**

In table 7 are the estimated probabilities that a given firm has 20% or more of their employees hired through flexible contracts for different values for 'digital means determining work tempo'. For each model which includes this variable the probability of a firm with the minimal score of 'digital means determining work tempo', a firm with the average score for reference, with the average score plus one to estimate a stepwise increase, and the probability of a firm with the maximal score. The minimum and maximum are used to estimate a maximum effect the variable can have. The average value of the centered variable 'digital means determining work tempo' is 0, the minimum is -1.22, the average plus one is 1, and the maximum is 4.78. The probabilities are all estimated by entering the aforementioned values, setting the dummies to the values appropriate for the reference category and then to solve for p.

The approach is similar in table 8. To test the moderator, the same conditional probabilities that a firm has 20% or more of their employees hired through flexible contracts are estimated as in table 7. However, in this case equations for model 3 and 4 are solved for all sectors. This way the difference of effects between sectors can be examined. The intensity of the moderator effect is tested by examining the difference of estimated probability ranges when the interaction term is included and excluded, i.e. by comparing model 4 with model 3 for each sector. In table 9 the effects of the control variables are evaluated for model 4. The variable 'digital means determining work tempo' is set to its average value (*mean* = 0). For each control variable the change of probability is estimated by solving the formula of model 4 for p when one of the dummy variables changes from the reference group.

**Conclusions on the research hypotheses**

The first hypothesis of this research is as follows:

H1: *As companies make more use of digital means which monitor/determine the work tempo, the proportion of flexible contracts is higher within those companies.*

The logistic regression analysis does not support this hypothesis. An initial significant negative effect was found in model 2 ($b$ = -0.080; $\chi^2(1)$ = 7.52; $p$ = 0.006), but the effect of the degree in which firms use digital means to determine the work tempo of employees needs to be tested by model 3 or 4 for the following two reasons: 1. The differences between sectors are significant as demonstrated by the Wald tests and the likelihood-ratio test of model 3 ($\chi^2(2)$ = 54.00; $p$ < 0.001). 2. The non-significant Hosmer-Lemeshow test of model 2 ($\chi^2(8)$ = 12.508; $p$ = 0.130) is disregarded, as argued in the model inspection paragraph. As can be seen in table 7 the maximal effect that 'digital means determining the work tempo' can have is seen in the row of model 4. The difference between the estimated probability that a given firm has 20% or more of their employees hired through flexible contracts is as follows; a firm for which all of the employees' work tempo is determined by digital means only has at most a 7.2 percentage point higher chance than a firm for which none of the employees' work tempo is determined by digital means. Further supported by the fact that the observed mean difference is insignificant in table 2 (*difference* = -0.03; $p$ = 0.72) and that in the partial regression plot given in appendix 3 (figure 3.2) the LOESS-curve is horizontal, it can be concluded that the effect of 'digital means determining the work tempo' on the 'use of flexible contracts' is non-existent given the logistic regression analysis.

The second hypothesis of this research is as follows:

H2: *The effect of digital means which monitor/determine the work tempo on the proportion of flexible contracts is different across sectors of establishments.*

This hypothesis is not strictly supported by the logistic regression in this research paper. The slopes of the interaction term for the construction sector ($b$ = -0.112; $p$ = 0.398) and that of the production sector ($b$ = 0.075; $p$ = 0.313) are small and insignificant. Upon closer inspection in table 8 it is however observed that the effect of the use of digital means determining the work tempo do make a little difference in the construction and production sectors. Especially in the construction sector the difference between the full range effects of digital means determining the work tempo is 11.7 percentage point, which is larger than the maximal effect which the predictor has on the use of flexible contracts (7.2 percentage point). It also includes a sign change, further supported by the fact the starting points of a firm using no digital means determining employees' work tempo is around the same probability. For production sectors this difference is a bit smaller (+5.9 pp). The services sector is very broadly defined so the result may not be very reliable. On the other hand, none of the probabilities exceed 50% and so neither the 'digital means determining work tempo' variable nor the 'sector of the establishment' interaction variables help to make differences in predictions. In short, the hypothesis is not supported but the models do reveal a possibility of differences in effects for more specific subdivisions of the sectors.

**Control variables and multicollinearity**

In table 9 the estimated probabilities of whether a given firm has hired 20% or more of their employees through flexible contract are given for each control variable. It is apparent that firms in the Netherlands have a much higher probability to fall in that category than firms in Belgium (-30.0pp) and Germany (-25.1pp). The slopes of Belgium ($b$ = -1.600; $p$ < 0.001) and Germany ($b$ = -1.229; $p$ < 0.001) are also significant in the model. The differences between Belgium and Germany may not be significant as the difference in probabilities is at most five percentage point. It seems that moderately large firms (50-249 employees) hire more employees through flexible contracts (+7.5pp; $b$ = 1.350; $p$ = 0.006) compared to small firms (10-49 employees). For large firms (250+ employees) this is even higher (+17.0pp; $b$ = 1.987; $p$ < 0.001). This increase in differences compared to the reference category as relatively larger firms are considered possibly implies the following; the more employees work at a given firm, the more likely that firm has a higher proportion of employees hired through flexible contracts.

In table 6 one can see that there is no significant effect of 'knowledge and skill volatility' for any of the categories. In table 9 all the differences in probabilities are small as well. The effects of this variable will not be interpreted. There are two reasons for this. The first reason is that the VIF-scores on the dummies for firms which required knowledge and skills of employees do not change very quickly (*VIF* = 7.174) and for those where they change fairly quickly (*VIF* = 6.962) too high. The threshold for VIF-scores in this research is that they must not exceed 4. The two aforementioned dummies vastly exceed that threshold and imply a strong multicollinearity with the other variables in the model. This means that the estimated effects attributed to these dummies are unreliable as they can be caused by the other variables in the model. The second reason why the effects won't be interpreted is that the only dummy with an unproblematic VIF-score is that of firms where the required knowledge and skills change very quickly (*VIF* = 1.621). As was explored in the univariate inspection, this category is too small to be considered representative for a generalizable effect (2.3% of observations). Considering this is not one of the main predictors of the research model its implications for the research will not be reflected upon, even though this outcome is unexpected due to the low association metrics observed in the bivariate inspection. The rest of the variables do not report a problematic VIF-score so there is no problem of multicollinearity troubling the interpretation of their effects.

*Table 7: Calculated probabilities for minimum, average, average +1 and maximum value of 'digital means determining work tempo' for models 2, 3 and 4.*

| | Minimum | Average | One point increase | Maximum |
|---|---|---|---|---|
| Model 2 | 41.5% | 39.2% | 37.3% | 30.5% |
| Model 3 | 44.4% | 43.5% | 42.8% | 40.3% |
| Model 4 | 44.9% | 43.4% | 42.2% | 37.7% |

*Note.* The reference category is a firm in the Netherlands with 10-49 employees of which the required skills do not change very quickly. In model 3 and 4 the reference category of 'sector of establishment' is service

*Table 8: Calculated probabilities for minimum, average, average +1 and maximum value of 'digital means determining work tempo' for each sector; comparing model 4 (including the interaction term) to model 3 (excluding the interaction term)*

| | | Minimum | Average | One point increase | Maximum | Difference of total range |
|---|---|---|---|---|---|---|
| Services sector (model reference) | Model 3 | 44.4% | 43.5% | 42.8% | 40.3% | |
| | Model 4 | 44.9% | 43.4% | 42.2% | 37.7% | -3.1 pp |
| Construction sector | Model 3 | 30.5% | 29.8% | 29.2% | 27.0% | |
| | Model 4 | 29.0% | 30.6% | 31.9% | 37.2% | +11.7 pp |
| Production sector | Model 3 | 25.3% | 24.6% | 24.1% | 22.2% | |
| | Model 4 | 23.1% | 23.7% | 24.1% | 25.9% | +5.9 pp |

*Note.* The reference category is a firm in the Netherlands with 10-49 employees of which the required skills do not change very quickly.

*Table 9: Probability differences for control variables compared to the reference firm for model 4.*

| | | Probability | Difference to reference (43.4%) |
|---|---|---|---|
| Country | *Belgium* | 13.4% | -30.0 pp |
| | *Germany* | 18.3% | -25.1 pp |
| Knowledge and skill volatility | *No change at all* | 50.9% | +7.5 pp |
| | *Fairly quickly* | 45.8% | +2.4 pp |
| | *Very quickly* | 40.8% | -2.6 pp |
| Company size | *50-249 employees* | 50.9% | +7.5 pp |
| | *250+ employees* | 60.4% | +17.0 pp |
| Sector of establishment | *Construction* | 30.6% | -12.8 pp |
| | *Production* | 23.7% | -19.7 pp |

*Note.* The reference category is a firm in the Netherlands with 10-49 employees of which the required skills do not change very quickly.

# Conclusion and discussion

The aim of this research was to give an answer to the question "*To what extent does the degree of work tempo monitoring through digital means relate to the use of flexible contracts by firms, and does this differ between sectors?*" Having considered firms of all sizes and sectors in the Netherlands, Belgium and Germany there seems to be no relation between the two firm strategies. A difference of effects between different sectors has not been observed in this research either, but there is indication these differences in effects may exist.

This means that within the framework of lean management, firm's operational optimization does not seem to take form in the combination of these two strategies; the use of work tempo monitoring technology and increasing numerical flexibility. The research demonstrates that the use of flexible contracts is largely explained by other factors. For example, factors specific to the Netherlands as firms in the Netherlands hire substantially more employees through flexible contracts, or by the size of the firm as this research shows that the larger the firm the more said firm hires employees through flexible contracts. However, before accepting the results as a confirmation of a directional relationship it needs to be remarked that the degree in which firms have flexibilized their workforce was measured using the (inverse) proportion of employees hired through open-ended contracts. This is a subset of the flexible periphery defined by Atkinson (1984); one that excludes independent contractors and platform workers as they are not hired through an employment contract. As this research is partially motivated by understanding the processes behind precaritization these workers are not ideally left out. On the other hand, research conducted by Koster (2022) implies that the exclusion of platform work does not necessarily pose a problem as he found that within platformed economies employers generally opt for high road strategies.

Koster (2022) also reasoned that technological innovation within firms gives them the opportunity to opt more for low road strategies. This research has found that for the application of work tempo monitoring technology there is seemingly no increase in use of flexible contracts; the use of flexible contracts reasoned to be a low road strategy. This could imply that firms may have the opportunity to do it but choose not to. Another possibility is that work tempo monitoring technology specifically does not give firms extra opportunities to opt for low road strategies, and that it is other types of technological innovation which gives room for this. The lack of a relation to work tempo monitoring technology may also be partially explained by the observed fact that at least half of the firms do not use this technology at all, so the anticipated effect may not have been able to take place for the firms in the dataset. While a difference of relationship between work sectors cannot be determined with the results of this research, it is possible that within specific sectors this combination of strategies is used. The more narrowly defined construction and production sectors seem to report a positive relationship. Notably in the construction sector it is possible that the optimization strategies of work tempo monitoring via digital means and use of flexible contracts are combined, but further research would be needed to confirm that.

**Limitations**

The scope of this research was limited to only examine the relation between work tempo monitoring technology and firm's use of flexible contracts in one direction. As the theoretical framework implies a non-directional relationship, the interpretation that there is no effect between the two would need to be corroborated with a similar research examining the relationship in the opposite direction. Another limitation was that the two main variables of the research were not measured as scales but as ordinal interval categorizations, this made them unsuitable for a linear regression analysis. This form of analysis would be preferable to measure a continuous effect. However, if more than three out of four firms have less than 20% of their employees hired through flexible contracts and at least half of the firms do not use work tempo monitoring technology the type of analysis may not have made a difference to begin with. To investigate whether the relationship differed between sectors the research was limited by the fact that the sectors of the establishment needed to be bundled together in three categories. In the final categorization the services sector comprised of ten of fifteen sectors. As a result it was disproportionately large and internally too diverse to make accurate statements regarding the effect within that bundle of sectors. The entertainment sector was in the same category as that of administrative work for example. This lead to a possible inaccurate estimation of the difference of effects between sectors.

A last context limitation may be that the data was gathered in 2019, which is the year the COVID-19 pandemic started. The pandemic ended up having lasting effects on the global economy, and in turn Europe's. The overall effects are complex but it may have had an effect in which firms choose for low or high road strategies. The pandemic particularly lead to labor shortages across the world including in Europe (Causa et al., 2022). This may have incentivized firms to improve their working conditions by opting for the high road. The labor shortages differ across sectors so this further stresses the necessity to focus on sectors separately in future research.

**Implications**

Despite the limitations of the research the conclusions yield implications for digitalization's effects on precaritization in Europe. Given that this research has not found a relationship between the use of work tempo monitoring technology and the use of flexible contracts by firms, this aspect of digitalization is in general not causing a second eroding of worker's bargaining position either. The dangers of alienation and deskilling are consequently also not intensified by the combination of these firm strategies. This however does not negate the possibility that these dangers may be linked by the two strategies separately. As has previously been addressed; workforce flexibilization as a low road strategy appears to be motivated by other factors. Hence, the process of precaritization is also caused by other processes in the labor market or within firms. This does not mean that the combination of work tempo monitoring technology and flexibilization strategies will never pose a problem in this respect. In this research it is observed that the vast majority of firms in the Netherlands, Belgium and Germany make no use of digital means that monitor and determine the work tempo of their employees. This may be true for firms all across Europe. Particular technologies like management by algorithms is also relatively new and not all firms may have access to them. As technological development continues in this regard these digital means may become more widely implemented as time progresses. It is possible that the fact that an effect has not been observed in this research because the effect has also not had enough time to occur throughout Europe.

**Recommendations for future research**

Throughout this chapter ideas for future research have already been hinted at. To reach a conclusive answer to the question whether the use of work tempo monitoring technology is combined with workforce flexibilization in the context of lean management strategies, the relationship needs to be analyzed bidirectionally. This could for example be done by corroborating this research with an analysis where the use of digital means determining the work tempo is treated as the outcome variable. Based on the implication that not enough time has passed for the relationship to form, another idea would be to conduct longitudinal research. This way it can be determined whether an increase in implementation of work tempo monitoring technology takes place, and whether that process ends up being paired with an increase of low road strategies by firms. Considering this research's limitation that work sectors had to be bundled together and that a possible difference of effects between sectors is observed, a multilevel analysis is recommended so that the effect can be determined for all fifteen work sectors separately. Running a multilevel analysis would also make the inclusion of all European countries possible. This way the results would be more generalizable.

More focused research is also recommended when it comes to determining what causes firms to opt for low road strategies and workforce flexibilization in particular. As this research indicates that the larger a firm is (i.e. the more employees a firm has) the higher the proportion of employees are hired through flexible contracts. For this reason future research could be focused exclusively on large firms. Specific causes of workforce flexibilization may also be found by solely studying firm strategies in the Netherlands as firms hire significantly more employees through flexible contracts there. In similar fashion, future research could also be focused on firms which make more use of work tempo monitoring technology. Given the implication that work tempo monitoring technology is new and possibly too expensive for relatively small firms, it is possible that large firms may make more use of it because they can afford it. This means that the expected relationship may be observed after all. It is also useful to take this approach when it comes to determining the difference between sectors. The possibility to monitor work tempo and the way in which work processes can be digitalized in general differs vastly for each sector.

Digitalization of labor is a process that does not stop. As new technologies develop, it remains crucial to monitor how firms integrate them if we are to safeguard job quality.

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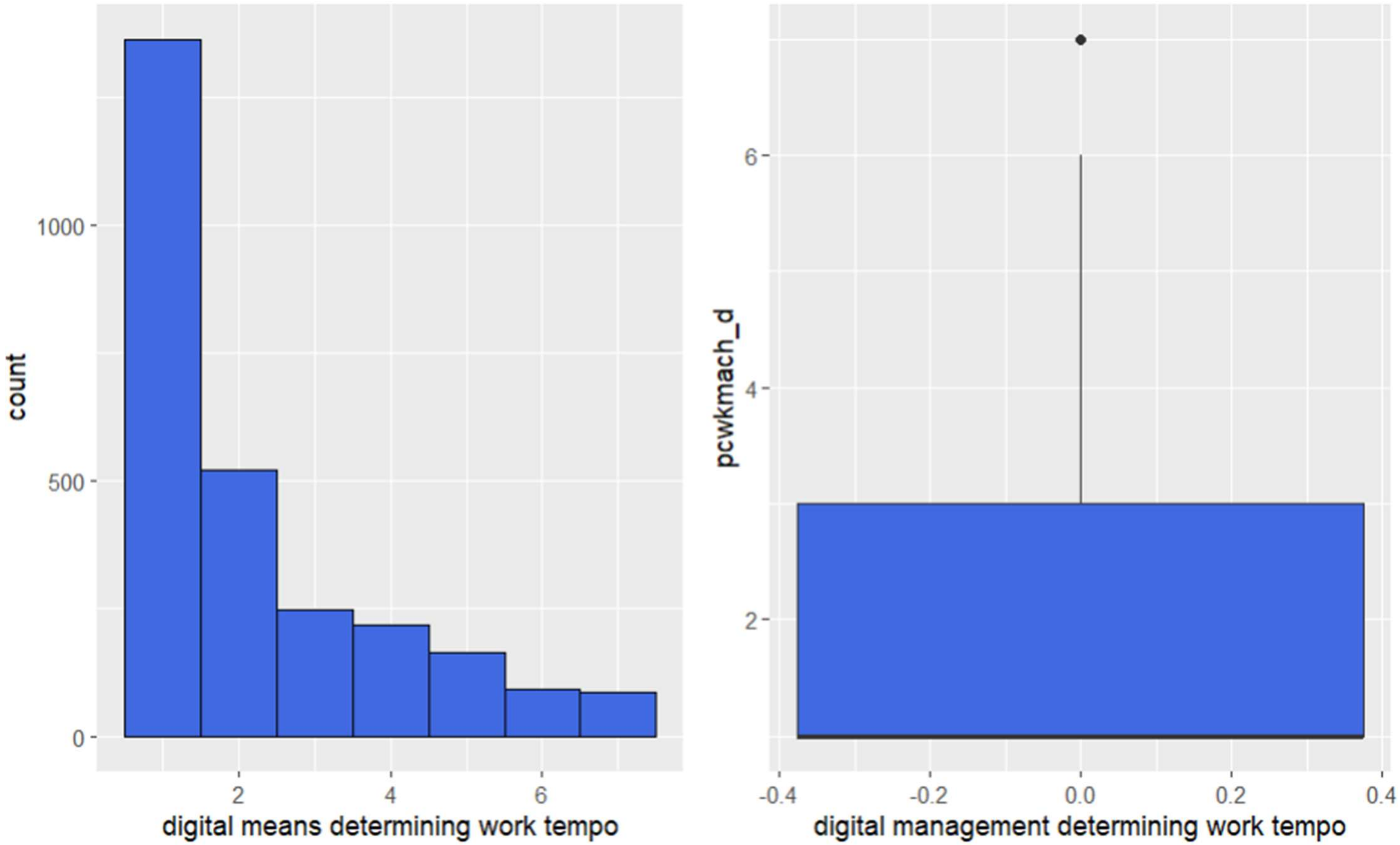
```
#------------------------------------------------------------------------------------
> #---------------------APPENDIX 1 VARIABLES AND THEIR CODING --------------------
> #----------------------------------------------------------------------------------
>
> #Loading packages
> library(tidyverse)
> library(gridExtra)
> library(gmodels)
> library(vcd)
> library(haven)
>
> #Importing the dataset
> thesisdata <- read_sav(
+   "C:/Users/arthu/Desktop/Sociologie/2025 Bachelorwerkstuk/ecs2019_mm_ukds.sav")
>
> #Filter to only include firms in the Netherlands, Belgium and Germany.\
> thesisdata <- thesisdata %>% filter(country == 2 |
+                                     country == 11 |
+                                     country == 20)
>
> #Command to count the missing values for each variable
>
> sum(is.na(thesisdata$pcwkmach_d))
[1] 43
> sum(is.na(thesisdata$empperm_d))
[1] 12
> sum(is.na(thesisdata$mm_sector_grp))
[1] 0
> sum(is.na(thesisdata$skillch))
[1] 14
> sum(is.na(thesisdata$est_size))
[1] 0
> sum(is.na(thesisdata$country))
[1] 0
>
> #Filter to remove the cases with at least one missing score on all variables.
> #The resulting data set will only contain cases with a valid score on each variable.
> thesisdata <- filter(thesisdata, !is.na(thesisdata$pcwkmach_d),
+                                  !is.na(thesisdata$empperm_d),
+                                  !is.na(thesisdata$mm_sector_grp),
+                                  !is.na(thesisdata$country),
+                                  !is.na(thesisdata$skillch),
+                                  !is.na(thesisdata$est_size))
>
> #################################################################
```

```
> #Variable-1:--------------digital means determining the work tempo---------------
>
> #Below are the lables (attributes) and the frequencies (tables) of this variable
>
> attributes(thesisdata$pcwkmach_d)
$label
[1] "[PCWKMACH and WPSIZE_MM] - For how many employees is the pace of work determined by machines or computers?"

$format.spss
[1] "F2.0"

$labels
      Skipped    None at all Less than 20%    20% to 39%    40% to 59%    60% to 79%    80% to 99%           All
           -3              1             2             3             4             5             6             7

$class
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$pcwkmach_d)

   1    2    3    4    5    6    7
1364  520  246  217  163   91   86
>
> #Commands to call the mean, the standard deviation and the five-number summary
> #(respectively)
>
> mean(thesisdata$pcwkmach_d, na.rm = TRUE)
[1] 2.222925
> sd(thesisdata$pcwkmach_d, na.rm = TRUE)
[1] 1.661785
> summary(thesisdata$pcwkmach_d)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   1.000   1.000   2.223   3.000   7.000
>
> #Command to create the histogram and boxplot for this variable
>
> h1 <- ggplot(thesisdata, mapping = aes(x = pcwkmach_d)) +
+        geom_histogram(bins = 7, color = "black", fill = "royalblue") +
+        xlab("digital means determining work tempo")
>
> b1 <- ggplot(data = thesisdata, mapping = aes(y = pcwkmach_d)) +
+         geom_boxplot(fill = "royalblue") +
+         xlab("digital means determining work tempo")
>
> grid.arrange(h1, b1, nrow = 1)
```

*Figure 1:Histogram and boxplot for the variable 'digital means determining work tempo' (N = 2687)*



```
> #Variable-2:---------------use of flexible contracts---------------
>
> #Below are the lables (attributes) and the frequencies (tables) of the original
> #values of the variable in the dataset which measures the proportion of open-ended
> #contracts.
>
> attributes(thesisdata$empperm_d)
$label
[1] "[EMPPERM and WPSIZE_MM] - How many employees in this establishment have an open-ended contract?"

$format.spss
[1] "F2.0"

$labels
      Skipped    None at all Less than 20%    20% to 39%    40% to 59%    60% to 79%    80% to 99%            All
           -3              1             2             3             4             5             6              7

$class
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$empperm_d)

   1    2    3    4    5    6    7 
  41  114  113  131  295 1113  880 
>
> #Code to dichotomize the variable into 0 '0% to 20% of employees are hired on flexible
> #contracts' and 1 'more than 20% of employees are hired on flexible contracts'.
> #The new variable will be called 'flexcontracts_bin'
>
> thesisdata <- thesisdata %>% mutate(flexcontracts_bin = ifelse(thesisdata$empperm_d < 6, 1, 0))
>
> #Frequencies (tables) of the resulting variable
>
> table(thesisdata$flexcontracts_bin)

   0    1 
1993  694 
>
```

```
> #Variable-3:--------------sector of the establishment---------------
>
> #Below are the lables (attributes) and the frequencies (tables) of this variable
>
> attributes(thesisdata$mm_sector_grp)
$label
[1] "MM Sector group"

$format.spss
[1] "F1.0"

$labels
           Ineligible Sector        Construction (NACE F)        Production (NACE B-E) Services (NACE G-N, R and S)
                           0                            1                            2                            3

$class
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$mm_sector_grp)

   1    2    3
 290  662 1735
>
> #Variable-4:--------------country---------------
>
> attributes(thesisdata$country)
$label
[1] "Country code"

$format.spss
[1] "F1.0"

$labels
        Austria         Belgium        Bulgaria         Croatia          Cyprus         Czechia         Denmark
              1               2               3               4               5               6               7
        Estonia         Finland          France         Germany          Greece         Hungary         Ireland
              8               9              10              11              12              13              14
          Italy          Latvia       Lithuania      Luxembourg           Malta     Netherlands          Poland
             15              16              17              18              19              20              21
       Portugal         Romania        Slovakia        Slovenia           Spain          Sweden  United Kingdom
             22              23              24              25              26              27              28
     Montenegro          Serbia North Macedonia          Turkey
             29              30              31              32

$class
```

```
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$country)

   2   11   20 
 979  688 1020 
> 
> #Variable-5:--------------knowledge and skill volatility---------------
> 
> attributes(thesisdata$skillch)
$label
[1] "How quickly do the knowledge and skills needed from the employees in this establishment change?"

$format.spss
[1] "F2.0"

$labels
         Skipped     Very quickly   Fairly quickly Not very quickly No change at all 
              -3                1                2                3                4 

$class
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$skillch)

   1    2    3    4 
  63  826 1707   91 
> 
```

```
> #Variable-6:--------------company size---------------
>
> attributes(thesisdata$est_size)
$label
[1] "Establishment size in number of employees"

$format.spss
[1] "F1.0"

$labels
   10 to 49 employees   50 to 249 employees 250 employees or more
                    1                     2                     3

$class
[1] "haven_labelled" "vctrs_vctr"     "double"

> table(thesisdata$est_size)

   1    2    3
1558  805  324
```

```
>
> #-------------------------------------------------------------------------------
> #---------------------APPENDIX 2 ANALYSES --------------------
> #-----------------------------------------------------------------------------
> #Loading packages
> library(tidyverse)
> library(gridExtra)
> library(gmodels)
> library(vcd)
> library(haven)
> library(rms)
> library(glmtoolbox)
>
> #Importing the dataset
> thesisdata <- read_sav(
+   "C:/Users/arthu/Desktop/Sociologie/2025 Bachelorwerkstuk/ecs2019_mm_ukds.sav")
>
> #Filter to only include firms in the Netherlands, Belgium and Germany.
> thesisdata <- thesisdata %>% filter(country == 2 |
+                                     country == 11 |
+                                     country == 20)
>
> #Filter to remove the cases with at least one missing score on all variables.
> #The resulting data set will only contain cases with a valid score on each variable.
> thesisdata <- filter(thesisdata, !is.na(thesisdata$pcwkmach_d),
+                                  !is.na(thesisdata$empperm_d),
+                                  !is.na(thesisdata$mm_sector_grp),
+                                  !is.na(thesisdata$country),
+                                  !is.na(thesisdata$skillch),
+                                  !is.na(thesisdata$est_size)
+                     )
>
> ######################################################################
>
> #Code to dichotomize the variable into 0 '0% to 20% of employees are hired on flexible
> #contracts' and 1 'more than 20% of employees are hired on flexible contracts'.
> #The new variable will be called 'flexcontracts_bin'
>
> thesisdata <- thesisdata %>% mutate(flexcontracts_bin = ifelse(thesisdata$empperm_d < 6, 1
, 0))
>
> #Construction of dummies for sector (moderator), the reference group is Services.
>
> thesisdata <- mutate(thesisdata,
```

```
+                        dummy_sect_contstr = ifelse(thesisdata$mm_sector_grp == 1, 1, 0))
> thesisdata <- mutate(thesisdata,
+                        dummy_sect_prod = ifelse(thesisdata$mm_sector_grp == 2, 1, 0))
>
> #Construction of dummies for country (control variable 1), the reference group is Netherla
nds.
>
> thesisdata <- mutate(thesisdata, dummy_Bel = ifelse(thesisdata$country == 2, 1, 0))
> thesisdata <- mutate(thesisdata, dummy_Ger = ifelse(thesisdata$country == 11, 1, 0))
>
> #Construction of dummies for knowledge and skill volatility (control variable 2),
> #the reference group is 'No change at all'.
>
> thesisdata <- mutate(thesisdata, dummy_sk_notveryq = ifelse(thesisdata$skillch == 3, 1, 0)
)
> thesisdata <- mutate(thesisdata, dummy_sk_fairlyq = ifelse(thesisdata$skillch == 2, 1, 0))
> thesisdata <- mutate(thesisdata, dummy_sk_veryq = ifelse(thesisdata$skillch == 1, 1, 0))
>
> #Construction of dummies for company size (control variable 3),
> #the reference group is '10 to 49 employees'.
>
> thesisdata <- mutate(thesisdata, dummy_size_med = ifelse(thesisdata$est_size == 2, 1, 0))
> thesisdata <- mutate(thesisdata, dummy_size_large = ifelse(thesisdata$est_size == 3, 1, 0)
)
>
> #Center independent variable 'digital means determining work tempo'.
> thesisdata <- mutate(thesisdata, dig_worktempo_c =
+                                    thesisdata$pcwkmach_d -
+                                    mean(thesisdata$pcwkmach_d))
>
> #Command to create the interaction terms for the regression analysis.
> thesisdata <- mutate(thesisdata, int_dwt_constr = thesisdata$dig_worktempo_c *
+                                    thesisdata$dummy_sect_contstr)
> thesisdata <- mutate(thesisdata, int_dwt_prod = thesisdata$dig_worktempo_c *
+                                    thesisdata$dummy_sect_prod)
>
>
> #------------------------BIVARIATE STATISTICS
>
> #Code to test the difference of variances. This information is needed for the
> #independent sample t-test.
>
> var.test(pcwkmach_d ~ flexcontracts_bin, data = thesisdata)
```

```
        F test to compare two variances

data:  pcwkmach_d by flexcontracts_bin
F = 1.0527, num df = 1992, denom df = 693, p-value = 0.4182
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.9297711 1.1874732
sample estimates:
ratio of variances
           1.05268

>
> #The variance of 'digital means determining work tempo' is not significantly different for
> #the two outcome groups of 'use of flexible contracts', hence equal variances
> #can be assumed for the t-test.
>
> #Independent sample t-test for mean difference of 'digital means determining work tempo' f
or
> #the two outcome groups of 'use of flexible contracts'.
>
> t.test(pcwkmach_d ~ flexcontracts_bin, data = thesisdata, var.equal= TRUE)

        Two Sample t-test

data:  pcwkmach_d by flexcontracts_bin
t = 0.36358, df = 2685, p-value = 0.7162
alternative hypothesis: true difference in means between group 0 and group 1 is not equal to
0
95 percent confidence interval:
 -0.1170103  0.1702789
sample estimates:
mean in group 0 mean in group 1
       2.229804        2.203170

>
> #Cross tables with chi^2-test results for the categorical variables;'sector of establishme
nt',
> #'country', 'knowledge and skill volatility' and 'company size'
>
> CrossTable(thesisdata$mm_sector_grp, thesisdata$country,
+             prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)
```

```
Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                         | thesisdata$country
thesisdata$mm_sector_grp |           2 |          11 |          20 |   Row Total |
-------------------------|-------------|-------------|-------------|-------------|
                       1 |         145 |          60 |          85 |         290 |
                         |      14.647 |       2.736 |       5.716 |             |
-------------------------|-------------|-------------|-------------|-------------|
                       2 |         204 |         209 |         249 |         662 |
                         |       5.737 |       9.203 |       0.021 |             |
-------------------------|-------------|-------------|-------------|-------------|
                       3 |         630 |         419 |         686 |        1735 |
                         |       0.007 |       1.434 |       1.139 |             |
-------------------------|-------------|-------------|-------------|-------------|
            Column Total |         979 |         688 |        1020 |        2687 |
-------------------------|-------------|-------------|-------------|-------------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  40.64036     d.f. =  4     p =  3.190433e-08
```

```
> CrossTable(thesisdata$mm_sector_grp, thesisdata$skillch,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                      | thesisdata$skillch
thesisdata$mm_sector_grp |         1 |         2 |         3 |         4 | Row Total |
-------------------------|-----------|-----------|-----------|-----------|-----------|
                       1 |         2 |        91 |       187 |        10 |       290 |
                         |     3.388 |     0.038 |     0.042 |     0.003 |           |
-------------------------|-----------|-----------|-----------|-----------|-----------|
                       2 |        11 |       178 |       453 |        20 |       662 |
                         |     1.317 |     3.196 |     2.503 |     0.261 |           |
-------------------------|-----------|-----------|-----------|-----------|-----------|
                       3 |        50 |       557 |      1067 |        61 |      1735 |
                         |     2.136 |     1.049 |     1.125 |     0.085 |           |
-------------------------|-----------|-----------|-----------|-----------|-----------|
            Column Total |        63 |       826 |      1707 |        91 |      2687 |
-------------------------|-----------|-----------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  15.14302     d.f. =  6     p =  0.01917304



> CrossTable(thesisdata$mm_sector_grp, thesisdata$est_size,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)
```

```
Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                         | thesisdata$est_size
thesisdata$mm_sector_grp |           1 |           2 |           3 | Row Total |
-------------------------|-------------|-------------|-------------|-----------|
                       1 |         198 |          83 |           9 |       290 |
                         |       5.299 |       0.173 |      19.285 |           |
-------------------------|-------------|-------------|-------------|-----------|
                       2 |         247 |         264 |         151 |       662 |
                         |      48.788 |      21.745 |      63.464 |           |
-------------------------|-------------|-------------|-------------|-----------|
                       3 |        1113 |         458 |         164 |      1735 |
                         |      11.380 |       7.345 |       9.769 |           |
-------------------------|-------------|-------------|-------------|-----------|
            Column Total |        1558 |         805 |         324 |      2687 |
-------------------------|-------------|-------------|-------------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  187.2479     d.f. =  4     p =  2.068427e-39
```

```
> CrossTable(thesisdata$mm_sector_grp, thesisdata$flexcontracts_bin,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                         | thesisdata$flexcontracts_bin
thesisdata$mm_sector_grp |         0 |         1 | Row Total |
-------------------------|-----------|-----------|-----------|
                       1 |       240 |        50 |       290 |
                         |     2.883 |     8.279 |           |
-------------------------|-----------|-----------|-----------|
                       2 |       543 |       119 |       662 |
                         |     5.503 |    15.803 |           |
-------------------------|-----------|-----------|-----------|
                       3 |      1210 |       525 |      1735 |
                         |     4.593 |    13.191 |           |
-------------------------|-----------|-----------|-----------|
            Column Total |      1993 |       694 |      2687 |
-------------------------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  50.25197     d.f. =  2     p =  1.224403e-11



> CrossTable(thesisdata$skillch, thesisdata$country,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)
```

```
Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                   | thesisdata$country
thesisdata$skillch |         2 |        11 |        20 | Row Total |
-------------------|-----------|-----------|-----------|-----------|
                 1 |        27 |        15 |        21 |        63 |
                   |     0.713 |     0.079 |     0.355 |           |
-------------------|-----------|-----------|-----------|-----------|
                 2 |       327 |       232 |       267 |       826 |
                   |     2.255 |     1.988 |     6.912 |           |
-------------------|-----------|-----------|-----------|-----------|
                 3 |       576 |       426 |       705 |      1707 |
                   |     3.393 |     0.281 |     5.016 |           |
-------------------|-----------|-----------|-----------|-----------|
                 4 |        49 |        15 |        27 |        91 |
                   |     7.572 |     2.957 |     1.648 |           |
-------------------|-----------|-----------|-----------|-----------|
      Column Total |       979 |       688 |      1020 |      2687 |
-------------------|-----------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  33.16906     d.f. =  6     p =  9.728884e-06
```

```
> CrossTable(thesisdata$skillch, thesisdata$est_size,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                   | thesisdata$est_size
thesisdata$skillch |         1 |         2 |         3 | Row Total |
-------------------|-----------|-----------|-----------|-----------|
                 1 |        36 |        18 |         9 |        63 |
                   |     0.008 |     0.040 |     0.259 |           |
-------------------|-----------|-----------|-----------|-----------|
                 2 |       474 |       237 |       115 |       826 |
                   |     0.051 |     0.442 |     2.381 |           |
-------------------|-----------|-----------|-----------|-----------|
                 3 |       980 |       532 |       195 |      1707 |
                   |     0.096 |     0.830 |     0.570 |           |
-------------------|-----------|-----------|-----------|-----------|
                 4 |        68 |        18 |         5 |        91 |
                   |     4.399 |     3.147 |     3.251 |           |
-------------------|-----------|-----------|-----------|-----------|
      Column Total |      1558 |       805 |       324 |      2687 |
-------------------|-----------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  15.47547     d.f. =  6     p =  0.01686409
```

```
> CrossTable(thesisdata$skillch, thesisdata$flexcontracts_bin,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                   | thesisdata$flexcontracts_bin
thesisdata$skillch |         0 |         1 | Row Total |
-------------------|-----------|-----------|-----------|
                 1 |        48 |        15 |        63 |
                   |     0.035 |     0.099 |           |
-------------------|-----------|-----------|-----------|
                 2 |       613 |       213 |       826 |
                   |     0.000 |     0.001 |           |
-------------------|-----------|-----------|-----------|
                 3 |      1265 |       442 |      1707 |
                   |     0.001 |     0.003 |           |
-------------------|-----------|-----------|-----------|
                 4 |        67 |        24 |        91 |
                   |     0.004 |     0.010 |           |
-------------------|-----------|-----------|-----------|
      Column Total |      1993 |       694 |      2687 |
-------------------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  0.152663     d.f. =  3     p =  0.9848429
```

```
> CrossTable(thesisdata$country, thesisdata$est_size,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                   | thesisdata$est_size
thesisdata$country |         1 |         2 |         3 | Row Total |
-------------------|-----------|-----------|-----------|-----------|
                 2 |       693 |       238 |        48 |       979 |
                   |    27.679 |    10.426 |    41.566 |           |
-------------------|-----------|-----------|-----------|-----------|
                11 |       365 |       209 |       114 |       688 |
                   |     2.885 |     0.040 |    11.614 |           |
-------------------|-----------|-----------|-----------|-----------|
                20 |       500 |       358 |       162 |      1020 |
                   |    14.133 |     8.991 |    12.372 |           |
-------------------|-----------|-----------|-----------|-----------|
      Column Total |      1558 |       805 |       324 |      2687 |
-------------------|-----------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  129.7061     d.f. =  4     p =  4.500503e-27



> CrossTable(thesisdata$country, thesisdata$flexcontracts_bin,
+            prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)
```

```
Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|


Total Observations in Table:  2687


                   | thesisdata$flexcontracts_bin
thesisdata$country |         0 |         1 | Row Total |
-------------------|-----------|-----------|-----------|
                 2 |       853 |       126 |       979 |
                   |    22.162 |    63.643 |           |
-------------------|-----------|-----------|-----------|
                11 |       562 |       126 |       688 |
                   |     5.237 |    15.040 |           |
-------------------|-----------|-----------|-----------|
                20 |       578 |       442 |      1020 |
                   |    42.140 |   121.017 |           |
-------------------|-----------|-----------|-----------|
      Column Total |      1993 |       694 |      2687 |
-------------------|-----------|-----------|-----------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  269.2397     d.f. =  2     p =  3.430363e-59



> CrossTable(thesisdata$est_size, thesisdata$flexcontracts_bin,
+             prop.r = FALSE, prop.c = FALSE, prop.t = FALSE, chisq = TRUE)


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|-------------------------|
```

```
Total Observations in Table:  2687

                     | thesisdata$flexcontracts_bin
thesisdata$est_size  |          0 |          1 |  Row Total |
---------------------|------------|------------|------------|
                   1 |       1211 |        347 |       1558 |
                     |      2.656 |      7.627 |            |
---------------------|------------|------------|------------|
                   2 |        577 |        228 |        805 |
                     |      0.676 |      1.940 |            |
---------------------|------------|------------|------------|
                   3 |        205 |        119 |        324 |
                     |      5.190 |     14.905 |            |
---------------------|------------|------------|------------|
        Column Total |       1993 |        694 |       2687 |
---------------------|------------|------------|------------|


Statistics for All Table Factors


Pearson's Chi-squared test
------------------------------------------------------------
Chi^2 =  32.99434     d.f. =  2     p =  6.844948e-08



>
>
> #Cramer's V scores for the categorical variables; 'sector of establishment', 'country',
> #'knowledge and skill volatility' and 'company size'
> assocstats(table(thesisdata$mm_sector_grp, thesisdata$country))$cramer
[1] 0.08696208
> assocstats(table(thesisdata$mm_sector_grp, thesisdata$skillch))$cramer
[1] 0.05308324
> assocstats(table(thesisdata$mm_sector_grp, thesisdata$est_size))$cramer
[1] 0.1866636
> assocstats(table(thesisdata$mm_sector_grp, thesisdata$flexcontracts_bin))$cramer
[1] 0.1367548
> assocstats(table(thesisdata$skillch, thesisdata$country))$cramer
[1] 0.07856295
```

```
> assocstats(table(thesisdata$skillch, thesisdata$est_size))$cramer
[1] 0.05366278
> assocstats(table(thesisdata$skillch, thesisdata$flexcontracts_bin))$cramer
[1] 0.0075376
> assocstats(table(thesisdata$country, thesisdata$est_size))$cramer
[1] 0.1553572
> assocstats(table(thesisdata$country, thesisdata$flexcontracts_bin))$cramer
[1] 0.3165452
> assocstats(table(thesisdata$est_size, thesisdata$flexcontracts_bin))$cramer
[1] 0.1108118
>
> #'digital management determining work tempo' conditional means and F-tests
> aggregate(pcwkmach_d ~ mm_sector_grp, data = thesisdata, mean)
  mm_sector_grp pcwkmach_d
1             1   1.810345
2             2   3.078550
3             3   1.965418
> summary(lm(pcwkmach_d ~ mm_sector_grp, thesisdata))

Call:
lm(formula = pcwkmach_d ~ mm_sector_grp, data = thesisdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.6260 -1.1018 -1.1018  0.6361  4.8982 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)    2.88817    0.12292  23.497  < 2e-16 ***
mm_sector_grp -0.26214    0.04678  -5.604 2.31e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.652 on 2685 degrees of freedom
Multiple R-squared:  0.01156,	Adjusted R-squared:  0.01119 
F-statistic:  31.4 on 1 and 2685 DF,  p-value: 2.309e-08

> aggregate(pcwkmach_d ~ country, data = thesisdata, mean)
  country pcwkmach_d
1       2   2.203269
2      11   1.879360
3      20   2.473529
> summary(lm(pcwkmach_d ~ country, thesisdata))
```

```
Call:
lm(formula = pcwkmach_d ~ country, data = thesisdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.3584 -1.2208 -1.0833  0.7792  4.9167 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.052720   0.055938  36.696  < 2e-16 ***
country     0.015282   0.004121   3.709 0.000213 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.658 on 2685 degrees of freedom
Multiple R-squared:  0.005097, Adjusted R-squared:  0.004726 
F-statistic: 13.75 on 1 and 2685 DF,  p-value: 0.0002125

> aggregate(pcwkmach_d ~ skillch, data = thesisdata, mean)
  skillch pcwkmach_d
1       1   2.428571
2       2   2.292978
3       3   2.197422
4       4   1.923077
> summary(lm(pcwkmach_d ~ skillch, thesisdata))

Call:
lm(formula = pcwkmach_d ~ skillch, data = thesisdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.4318 -1.1831 -1.0587  0.8169  4.9413 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.55614    0.15230  16.784   <2e-16 ***
skillch     -0.12435    0.05556  -2.238   0.0253 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.661 on 2685 degrees of freedom
Multiple R-squared:  0.001862, Adjusted R-squared:  0.00149 
F-statistic: 5.009 on 1 and 2685 DF,  p-value: 0.0253
```

```
> aggregate(pcwkmach_d ~ est_size, data = thesisdata, mean)
  est_size pcwkmach_d
1        1   2.012195
2        2   2.468323
3        3   2.626543
> summary(lm(pcwkmach_d ~ est_size, thesisdata))

Call:
lm(formula = pcwkmach_d ~ est_size, data = thesisdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.7323 -1.0342 -1.0342  0.6168  4.9658 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.68514    0.07671   21.97  < 2e-16 ***
est_size     0.34904    0.04533    7.70  1.9e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.644 on 2685 degrees of freedom
Multiple R-squared:  0.0216,	Adjusted R-squared:  0.02124 
F-statistic: 59.29 on 1 and 2685 DF,  p-value: 1.903e-14

> 
> 
> #----------------------REGRESSION ANALYSIS --------------------------
> #explanation: I estimate four models.See below
> 
> model0 <- glm(flexcontracts_bin ~ 1,
+                 family = binomial (link = "logit"), data = thesisdata)
> model1 <- glm(flexcontracts_bin ~ dummy_Bel + dummy_Ger +
+                  dummy_sk_notveryq + dummy_sk_fairlyq + dummy_sk_veryq +
+                  dummy_size_med + dummy_size_large,
+                 family = binomial (link = "logit"), data = thesisdata)
> model2 <- glm(flexcontracts_bin ~ dummy_Bel + dummy_Ger +
+                  dummy_sk_notveryq + dummy_sk_fairlyq + dummy_sk_veryq +
+                  dummy_size_med + dummy_size_large +
+                  dig_worktempo_c,
+                family = binomial (link = "logit"), data = thesisdata)
> model3 <- glm(flexcontracts_bin ~ dummy_Bel + dummy_Ger +
+                  dummy_sk_notveryq + dummy_sk_fairlyq + dummy_sk_veryq +
+                  dummy_size_med + dummy_size_large +
```

```
+                dig_worktempo_c +
+                dummy_sect_contstr + dummy_sect_prod,
+               family = binomial (link = "logit"), data = thesisdata)
> model4 <- glm(flexcontracts_bin ~ dummy_Bel + dummy_Ger +
+                dummy_sk_notveryq + dummy_sk_fairlyq + dummy_sk_veryq +
+                dummy_size_med + dummy_size_large +
+                dig_worktempo_c +
+                dummy_sect_contstr + dummy_sect_prod +
+                int_dwt_constr + int_dwt_prod,
+               family = binomial (link = "logit"), data = thesisdata)
>
> #Extracting the model coefficients and deviance for models 1 to 4 respectively.
> summary(model1)

Call:
glm(formula = flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large,
    family = binomial(link = "logit"), data = thesisdata)

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.1246     0.2606  -0.478  0.63267
dummy_Bel          -1.6018     0.1170 -13.686  < 2e-16 ***
dummy_Ger          -1.2399     0.1179 -10.514  < 2e-16 ***
dummy_sk_notveryq  -0.3085     0.2603  -1.185  0.23602
dummy_sk_fairlyq   -0.1783     0.2671  -0.668  0.50443
dummy_sk_veryq     -0.3062     0.4031  -0.760  0.44747
dummy_size_med      0.1424     0.1051   1.355  0.17553
dummy_size_large    0.4469     0.1393   3.208  0.00133 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3069.9  on 2686  degrees of freedom
Residual deviance: 2789.6  on 2679  degrees of freedom
AIC: 2805.6

Number of Fisher Scoring iterations: 4
```

```
> exp(coef(model1))
      (Intercept)         dummy_Bel         dummy_Ger dummy_sk_notveryq  dummy_sk_fairlyq
dummy_sk_veryq
        0.8828786         0.2015345         0.2894013         0.7345507         0.8366874
0.7362153
   dummy_size_med  dummy_size_large
        1.1530485         1.5633875
> summary(model2)

Call:
glm(formula = flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c, family = binomial(link = "logit"), data = thesisdata)

Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)       -0.14069    0.26040  -0.540 0.589004
dummy_Bel         -1.62020    0.11754 -13.785  < 2e-16 ***
dummy_Ger         -1.28920    0.11958 -10.781  < 2e-16 ***
dummy_sk_notveryq -0.29838    0.25994  -1.148 0.251015
dummy_sk_fairlyq  -0.15602    0.26679  -0.585 0.558682
dummy_sk_veryq    -0.27876    0.40389  -0.690 0.490084
dummy_size_med     0.18043    0.10621   1.699 0.089366 .
dummy_size_large   0.49697    0.14091   3.527 0.000421 ***
dig_worktempo_c   -0.08027    0.02971  -2.702 0.006895 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3069.9  on 2686  degrees of freedom
Residual deviance: 2782.1  on 2678  degrees of freedom
AIC: 2800.1

Number of Fisher Scoring iterations: 4

> exp(coef(model2))
      (Intercept)         dummy_Bel         dummy_Ger dummy_sk_notveryq  dummy_sk_fairlyq
dummy_sk_veryq
        0.8687601         0.1978584         0.2754921         0.7420221         0.8555412
0.7567243
   dummy_size_med  dummy_size_large   dig_worktempo_c
        1.1977346         1.6437296         0.9228633
> summary(model3)
```

```
Call:
glm(formula = flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod, family = binomial(link = "logit"
),
    data = thesisdata)

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.04438    0.26440   0.168  0.86670
dummy_Bel          -1.59551    0.11842 -13.473  < 2e-16 ***
dummy_Ger          -1.23238    0.12099 -10.186  < 2e-16 ***
dummy_sk_notveryq  -0.30396    0.26259  -1.158  0.24705
dummy_sk_fairlyq   -0.21278    0.26973  -0.789  0.43018
dummy_sk_veryq     -0.41768    0.40739  -1.025  0.30524
dummy_size_med      0.30455    0.10841   2.809  0.00497 **
dummy_size_large    0.68823    0.14721   4.675 2.94e-06 ***
dig_worktempo_c    -0.02825    0.03064  -0.922  0.35665
dummy_sect_contstr -0.59853    0.17324  -3.455  0.00055 ***
dummy_sect_prod    -0.85911    0.12978  -6.620 3.60e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3069.9  on 2686  degrees of freedom
Residual deviance: 2728.1  on 2676  degrees of freedom
AIC: 2750.1

Number of Fisher Scoring iterations: 4

> exp(coef(model3))
       (Intercept)          dummy_Bel          dummy_Ger  dummy_sk_notveryq   dummy_sk_fairl
yq     dummy_sk_veryq
         1.0453789          0.2028059          0.2915981          0.7378910          0.80833
11          0.6585735
    dummy_size_med   dummy_size_large    dig_worktempo_c dummy_sect_contstr    dummy_sect_pr
od
         1.3560160          1.9901840          0.9721499          0.5496163          0.42353
72
> summary(model4)
```

```
Call:
glm(formula = flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod +
    int_dwt_constr + int_dwt_prod, family = binomial(link = "logit"),
    data = thesisdata)

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.03595    0.26466   0.136  0.89197
dummy_Bel          -1.60031    0.11858 -13.496  < 2e-16 ***
dummy_Ger          -1.22867    0.12113 -10.143  < 2e-16 ***
dummy_sk_notveryq  -0.29988    0.26281  -1.141  0.25385
dummy_sk_fairlyq   -0.20550    0.27001  -0.761  0.44661
dummy_sk_veryq     -0.41038    0.40757  -1.007  0.31398
dummy_size_med      0.30010    0.10860   2.763  0.00572 **
dummy_size_large    0.68643    0.14727   4.661 3.15e-06 ***
dig_worktempo_c    -0.04989    0.03576  -1.395  0.16293
dummy_sect_contstr -0.55646    0.17952  -3.100  0.00194 **
dummy_sect_prod    -0.90594    0.14185  -6.386 1.70e-10 ***
int_dwt_constr      0.11167    0.13224   0.844  0.39841
int_dwt_prod        0.07527    0.07457   1.009  0.31277
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3069.9  on 2686  degrees of freedom
Residual deviance: 2726.6  on 2674  degrees of freedom
AIC: 2752.6

Number of Fisher Scoring iterations: 4

> exp(coef(model4))
       (Intercept)          dummy_Bel          dummy_Ger  dummy_sk_notveryq   dummy_sk_fairl
yq     dummy_sk_veryq
         1.0365999          0.2018332          0.2926802          0.7409077          0.81424
39          0.6633962
    dummy_size_med   dummy_size_large    dig_worktempo_c dummy_sect_contstr    dummy_sect_pr
od     int_dwt_constr
         1.3499877          1.9866076          0.9513333          0.5732342          0.40416
03          1.1181446
      int_dwt_prod
         1.0781748
```

```
>
> #Anova tables and likelihood ratio tests for models 1 to 4 respectively.
> anova(model0, model1, test = "LRT")
Analysis of Deviance Table

Model 1: flexcontracts_bin ~ 1
Model 2: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large
  Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
1      2686     3069.9
2      2679     2789.6  7   280.26 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(model1, model2, test = "LRT")
Analysis of Deviance Table

Model 1: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large
Model 2: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c
  Resid. Df Resid. Dev Df Deviance Pr(>Chi)
1      2679     2789.6
2      2678     2782.1  1   7.5233 0.006091 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(model2, model3, test = "LRT")
Analysis of Deviance Table

Model 1: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c
Model 2: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod
  Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
1      2678     2782.1
2      2676     2728.1  2   53.993 1.886e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> anova(model3, model4, test = "LRT")
Analysis of Deviance Table

Model 1: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
```

```
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod
Model 2: flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod +
    int_dwt_constr + int_dwt_prod
  Resid. Df Resid. Dev Df Deviance Pr(>Chi)
1      2676     2728.1
2      2674     2726.6  2   1.5233   0.4669
>
> #Hosmer-Lemeshow tests for models 1 to 4 respectively.
> hltest(model1)

   The Hosmer-Lemeshow goodness-of-fit test

 Group Size Observed  Expected
     1  401       50  46.35211
     2  256       42  32.92513
     3  263       26  36.30348
     4  266       30  42.38695
     5  264       53  46.67782
     6  217       51  47.35452
     7  352      135 138.47503
     8  381      161 162.34467
     9  287      146 141.18030

         Statistic =  12.77987
degrees of freedom =  7
           p-value =  0.077657
```

```
> hltest(model2)

   The Hosmer-Lemeshow goodness-of-fit test

 Group Size Observed  Expected
     1  268       31  27.97298
     2  273       39  33.64744
     3  278       44  37.63786
     4  229       31  34.77773
     5  253       26  42.32641
     6  272       57  52.80484
     7  270       83  85.66276
     8  313      122 128.42331
     9  307      142 136.43280
    10  224      119 114.31388

         Statistic =  12.50814
degrees of freedom =  8
           p-value =  0.12993

> hltest(model3)

   The Hosmer-Lemeshow goodness-of-fit test

 Group Size Observed  Expected
     1  271       28  19.90815
     2  268       29  28.32355
     3  292       43  39.80204
     4  275       43  42.62182
     5  269       40  49.84311
     6  259       55  59.42084
     7  272       80  82.29940
     8  225       82  92.47159
     9  273      123 123.59433
    10  265      166 144.30330
    11   18        5  11.41184

         Statistic =  25.79786
degrees of freedom =  9
           p-value =  0.0022045
```

```
> hltest(model4)

   The Hosmer-Lemeshow goodness-of-fit test

 Group Size Observed   Expected
     1  273       28  19.878009
     2  267       29  27.593878
     3  313       45  42.739318
     4  264       44  41.335850
     5  272       40  51.134913
     6  279       59  65.802858
     7  273       77  87.321062
     8  201       84  83.220341
     9  268      121 122.444463
    10  271      167 148.661008
    11    6        0   3.868301

         Statistic =  25.64438
degrees of freedom =  9
           p-value =  0.0023352

>
> #Creation of function for classification tables
> Class.table <- function(LOGMOD = NULL){
+   library(tidyverse)
+   DATSET <- LOGMOD$data
+   DATSET <- mutate(DATSET,
+                    p_hat = predict(LOGMOD, type = "response"),
+                    y_hat = as.factor(ifelse(p_hat >= 0.5, 1, 0)))
+   DV <- LOGMOD$formula[[2]]
+   Class_tmp <- table(DATSET[[DV]], DATSET$y_hat)
+   Class_tab <- matrix(data = NA, nrow = 3, ncol = 3)
+   # Controle of alle cases in 1 groep geclassificeerd worden
+   C1 <- ifelse(Class_tmp[1]+Class_tmp[2] == length(DATSET[[DV]]), T, F)
+   # Controle of dit de 0 groep is (anders 1)
+   C2 <- ifelse(dimnames(Class_tmp)[[2]] == "0", T, F)
+
+   if(C1){
+     Class_tab[1,1] <- ifelse(C2, Class_tmp[1], 0)
+     Class_tab[1,2] <- ifelse(C2, 0, Class_tmp[1])
+     Class_tab[2,1] <- ifelse(C2, Class_tmp[2], 0)
+     Class_tab[2,2] <- ifelse(C2, 0, Class_tmp[2])
+   } else {
+     Class_tab[1:2,1:2] <- Class_tmp
```

```
+   }
+
+   Class_tab[1,3] <- round(Class_tab[1,1] / (Class_tab[1,1] + Class_tab[1,2]), 4)
+   Class_tab[2,3] <- round(Class_tab[2,2] / (Class_tab[2,1] + Class_tab[2,2]), 4)
+   Class_tab[3,3] <- round((Class_tab[1,1] + Class_tab[2,2]) / length(DATSET[[DV]]), 4)
+   rownames(Class_tab) <- c("Obs0", "Obs1", "Tot")
+   colnames(Class_tab) <- c("Exp0", "Exp1", "Tot")
+
+   return(Class_tab)
+ }
>
> #Calling classification tables for models 2 and 4.
> Class.table(model2)
     Exp0 Exp1    Tot
Obs0 1942   51 0.9744
Obs1  629   65 0.0937
Tot    NA   NA 0.7469
> Class.table(model4)
     Exp0 Exp1    Tot
Obs0 1900   93 0.9533
Obs1  541  153 0.2205
Tot    NA   NA 0.7640
>
> #Variance inflation factor (VIF) scores for coefficients of model 4
> vif(model4)
         dummy_Bel          dummy_Ger  dummy_sk_notveryq   dummy_sk_fairlyq     dummy_sk_ver
yq     dummy_size_med
          1.152949           1.140835           7.173949           6.961546           1.6212
43          1.156367
  dummy_size_large    dig_worktempo_c dummy_sect_contstr    dummy_sect_prod     int_dwt_cons
tr        int_dwt_prod
          1.206405           1.555781           1.107180           1.433321           1.1576
36          1.710425
>
> #Calculation of leverages
> thesisdata <- thesisdata %>% mutate(leverage = hatvalues(model4))
>
> #Filtering the dataset for cases with extreme leverage values. Threshold is
> #calculated as 3*(number of parameters)/(sample size)
> thesisdata_extreme <- filter(thesisdata, thesisdata$leverage < 0.0134)
>
> #Estimation of complete model excluding cases with extreme leverage values.
> model5 <- glm(flexcontracts_bin ~ dummy_Bel + dummy_Ger +
+                 dummy_sk_notveryq + dummy_sk_fairlyq + dummy_sk_veryq +
```

```
+                 dummy_size_med + dummy_size_large +
+                 dig_worktempo_c +
+                 dummy_sect_contstr + dummy_sect_prod +
+                 int_dwt_constr + int_dwt_prod,
+               family = binomial (link = "logit"), data = thesisdata_extreme)
>
> summary(model5)

Call:
glm(formula = flexcontracts_bin ~ dummy_Bel + dummy_Ger + dummy_sk_notveryq +
    dummy_sk_fairlyq + dummy_sk_veryq + dummy_size_med + dummy_size_large +
    dig_worktempo_c + dummy_sect_contstr + dummy_sect_prod +
    int_dwt_constr + int_dwt_prod, family = binomial(link = "logit"),
    data = thesisdata_extreme)

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.44170    0.54417  -0.812  0.41697
dummy_Bel          -1.54521    0.12261 -12.603  < 2e-16 ***
dummy_Ger          -1.19397    0.12413  -9.619  < 2e-16 ***
dummy_sk_notveryq   0.15270    0.54080   0.282  0.77767
dummy_sk_fairlyq    0.24814    0.54348   0.457  0.64798
dummy_sk_veryq     -0.28279    0.91054  -0.311  0.75613
dummy_size_med      0.28946    0.11172   2.591  0.00957 **
dummy_size_large    0.76993    0.15228   5.056 4.28e-07 ***
dig_worktempo_c    -0.05275    0.03664  -1.439  0.15002
dummy_sect_contstr -0.32497    0.21230  -1.531  0.12584
dummy_sect_prod    -0.93284    0.14534  -6.418 1.38e-10 ***
int_dwt_constr      0.39226    0.19753   1.986  0.04705 *
int_dwt_prod        0.09238    0.07813   1.182  0.23703
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2915.8  on 2566  degrees of freedom
Residual deviance: 2590.5  on 2554  degrees of freedom
AIC: 2616.5

Number of Fisher Scoring iterations: 4
```

# Appendix 3: Data exploration

In this appendix the original data exploration will be shown and the resulting argument for dichotomizing the dependent variable 'use of flexible contracts'.

**Assumptions of linear regression**

The original plan of analysis was to test the hypotheses by means of linear regression. After estimating the linear models the assumptions of linear regression analysis were controlled for. The results are described below. To prevent repetition with the main body of the paper the assumption which states that all observed values are independent of other observed values is disregarded in this appendix.

*Linearity of relationship*

One of the assumptions of linear regression is that the relation between the independent variable and the dependent variable is in fact linear. This assumption can be tested by examining the residual plot. Figure 1 shows the residual plot of the linear regression analysis. On the x-axis are the fitted values, the values of data points predicted by the model, on the y-axis are the residuals. If for all predictions the average value of the residuals is zero that means the linear model fits the data, which is only possible if the relation between the dependent variable and the independent variables is linear. The red line going through the plotted residuals is the LOESS-curve, this gives the conditional means of the residuals for the fitted values. The curve demonstrates that for all fitted variables the average of the residual is consistently slightly lower than zero. It reaches around -0.4 for most predictions. The dependent variable has a seven point scale so this is potentially problematic. To further inspect the linear relation between the dependent variable and the main predictor 'digital means determining work tempo' are plotted against each other in figure 2. The red line through the scatterplot is again a LOESS-curve. It shows that the conditional means for the use of flexible contracts does not change for different degrees of use of digital means that determine work tempo. This would mean that a potential linear regression model will tend to be flat. This plot also shows based on the spread of datapoints that a linear model would not fit the data very well; the data is heavily skewed for both of the variables in the model. In conclusion the assumption of a linear relation is credibly violated.

*Homoscedasticity*

Another assumption of linear regression is that the standard deviation of the residuals is constant for all predictions, called homoscedasticity. This assumption can also be tested by examining the residual plot in figure 1. The fact that the possible values of the dependent variables is limited to seven makes it harder to eyeball the spread in certain parts of the plot. The spread does seem to fluctuate; for the lowest fitted values the spread is relatively small, mostly yielding residuals close to zero. Following the x-axis towards the fitted value of 2 the spread seems to increase as the amount of large positive residuals increases. After a brief decrease beyond that, because residuals start to concentrate around zero, it is again large around the fitted value of 2.7. The amount of relatively lower (negative) residuals seems to decrease gradually as fitted values increase. For fitted values of 2.8 and higher the spread of residuals remains relatively large compared to lower fitted values. Despite there being less datapoints for higher fitted values a clear spread can be observed. This assumption regarding homoscedasticity is violated.

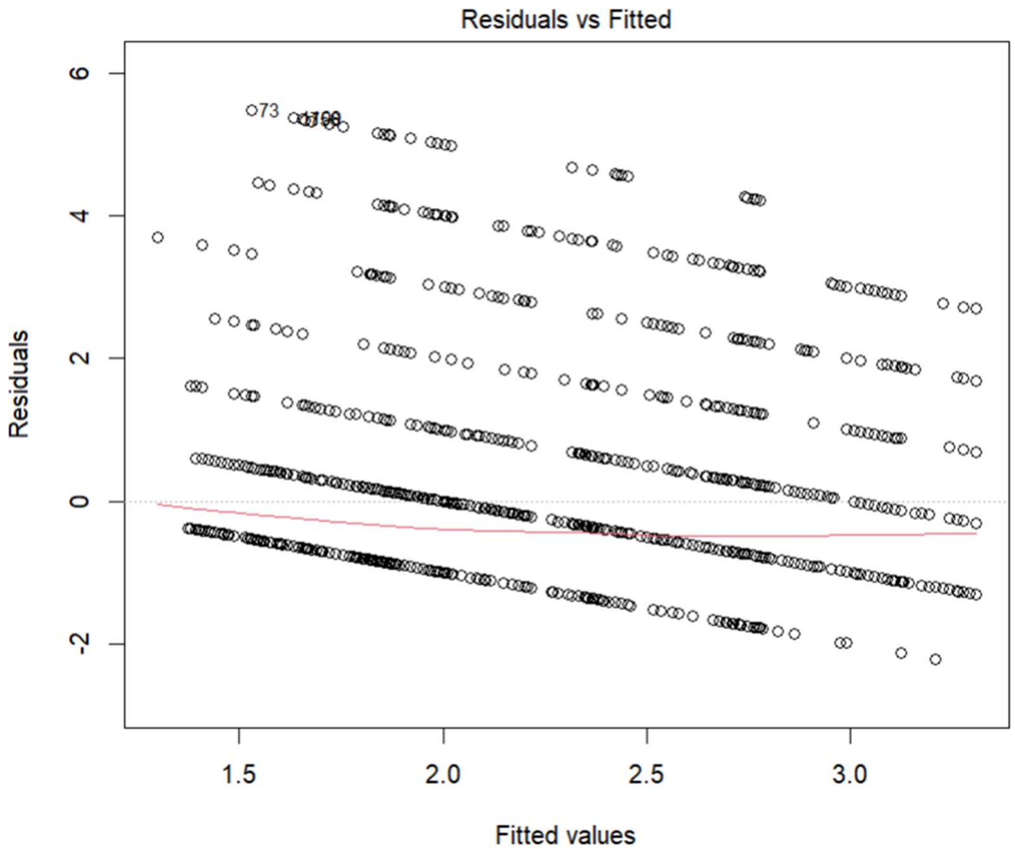



*Figure 3.2: Residual plot of linear model with fitted loess-curve*

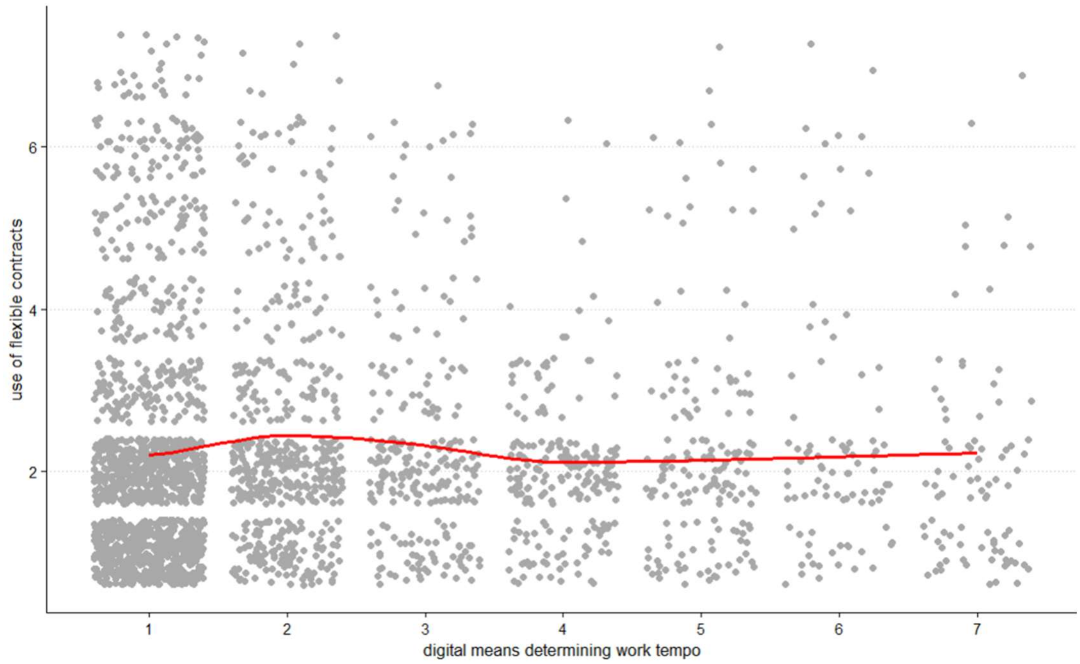



*Figure 3.3: Scatterplot between 'digital means determining work tempo' and 'use of flexible contracts' with fitted loess-curve*

*Normal distribution of residuals*

The last assumption of linear regression which needs to be considered is that the residuals of the linear model ought to be normally distributed. This assumption can be tested by examining the QQ-plot given in figure 3. The residuals would be normally distributed if the values of standardized residuals follow the diagonal across the quantiles given on the x-axis. The standardized residuals only follow the diagonal reasonably well for quantiles -2 to around 1. They only slightly deviate for lower quantiles, but they deviate extremely for quantiles 2 to 3. This assumption is hence violated.

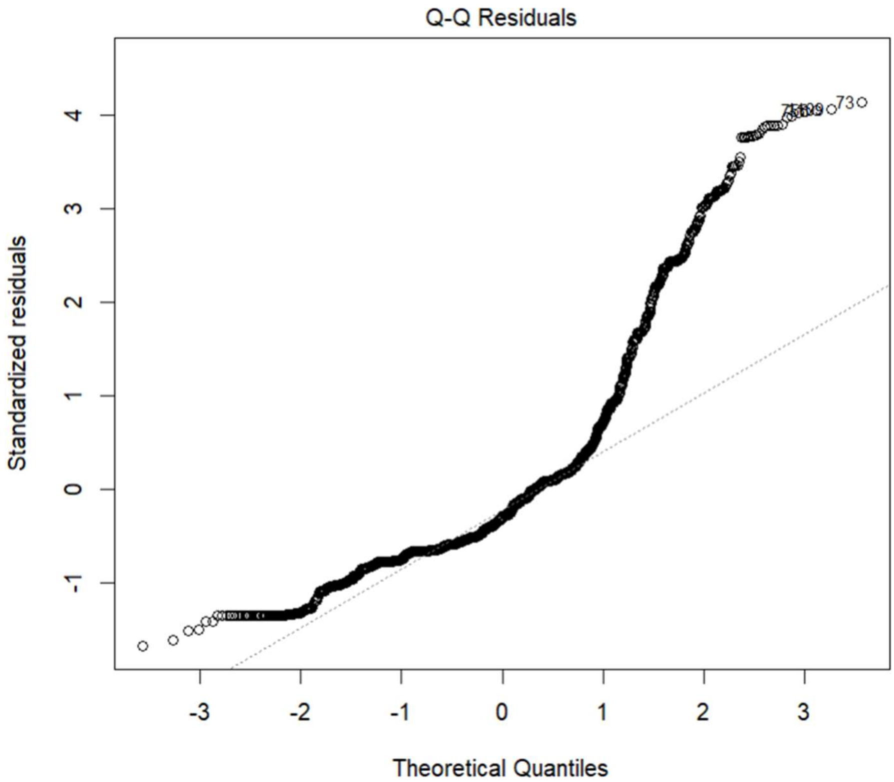



*Figure 3.4: QQ-plot of the linear regression model*

**Dichotomization**

As most assumptions of linear regression have been violated it seems to be more appropriate to test the research hypotheses through a logistic regression analysis. The dependent variable 'use of flexible contracts' is dichotomized using a median split. In table 1 the distribution of the original variable is given. The decision to count the median as the low category or the high category is an important one because the median, the category 'less than 20%', accounts for 41.2% of the data. In both cases the split will be uneven; in the case the median will we coded as the low value, the ratio of low to high scores on the dichotomized variable would be around three to one. In the case the median will be coded as the high value this ratio would be around one to two. To make the split as even as possible the median of the original variable should be coded as the high value.

However, based on the original operationalization of the variable and on the focus of the research paper it makes more sense to count the median as a low value. As can be seen in table 1 the original operationalization of the lowest values of 'use of flexible contracts' are 'none at all' and 'less than 20%'. If the former category is the only one coded as the low value and all the other categories as the high value, the logistical regression model would predict probabilities whether certain firms use flexible labor at all or not at all. Considering the research is meant to explain a difference in the degree flexible labor is used for different firms, and not to explain which firms use flexible labor and which firms do not, it is more appropriate to split the outcome variable as a dichotomy of firms in which 20% or fewer of total employees are hired through flexible contracts and firms in which 20% or more of the total employees are hired through flexible contracts. Hence, the dichotomous dependent variable is operationalized as follows; 'use of flexible contracts' takes the value 0 for category 'less than 20%' and the value 1 for category '20% or more'.

*Table 3.1: Frequency table for continuous variable 'use of flexible contracts' (N=2687)*

| | Category | Frequency | Percentage | Cumulative percentage |
|---|---|---|---|---|
| Use of flexible contracts | None at all | 880 | 32.8% | 32.8% |
| | Less than 20% | 1113 | 41.4% | 74.2% |
| | 20% to 39% | 295 | 11.0% | 85.2% |
| | 40% to 59% | 131 | 4.9% | 90.0% |
| | 60% to 79% | 113 | 4.2% | 94.2% |
| | 80% to 99% | 114 | 4.2% | 98.5% |
| | All | 41 | 1.5% | 100% |