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Delivering Food in the Gig Economy

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Abstract

The internet has opened new opportunities to match the supply of and demand for labour. Through online platforms, work is allocated to workers looking for one-time service jobs. This phenomenon is called 'the gig economy'. The increased flexibility of gig work often comes at a price: in the gig economy, workers are often treated as independent contractors by the platforms, which implies limited job security, insurance coverage and lacking access to social security. This thesis explores the trade-off regarding on the one hand the lack of insurance and the decline of social security in gig work and on the other hand the increase in job flexibility and income. It does so by analysing how different levels of flexibility, security, and payment influence the choice of job of workers. Two groups of workers can be distinguished in the gig economy. The first group is the freelancing gig workers, who have an independent contractor relation with the platform. The second group, the hired gig workers, work via a so-called on-call min/max-contract relationships. Data on these groups' preferences was gathered through a discrete choice survey. In this survey, several configurations of work arrangements with differing social security, income and flexibility levels have been presented to the respondents, who were then asked to express their preferences. The survey has been conducted amongst 102 workers in the food delivery industry in the Netherlands.

Using a conditional logistic regression model, it is shown that freelancing gig workers prefer payment per delivery and work on-demand more than hired gig workers. Preferences do not differ between hired workers and freelancers regarding sick pay and accident insurance coverage. Two recommendations are given based on these findings: First, the government should introduce a basic social security system for independent contractors to ensure the well-being of the freelancers and counter "race-to-the-bottom" of work conditions. Second, independent contractors should unify and demand work conditions that align with their preferences.

Contents

1. Introduction

Since its invention, the internet has changed many aspects of our daily lives, including the labour market. One-time service jobs mediated via online platforms, such as Helpling, Uber and Deliveroo, are increasingly being used as a way of earning a living. These platforms are used by a growing amount of people in the Netherlands (Huws, Spencer & Joyce, 2016), as well as worldwide (Aloisi, 2015). This phenomenon is called 'the gig economy'. In the gig economy, small one-time tasks (gigs) are performed by workers (gig workers) who are only for the duration of the task formally connected to the organisation that they perform the task for (Abraham, Haltiwanger, Sandusky & Spletzer, 2017).

Within current legislative structures, gig workers are often classified as independent contractors, which leads to an increase in flexibility of when and where a worker works (De Stefano, 2015). This often results in gig workers having little access to social security and poor insurance for accidents (Aloisi, 2015; Witteman, 2017b). A perceived benefit of the gig economy is a possible increase of income and more flexibility, which provides room for gig workers to spend time on studying, family or leisure activities (Harris and Krueger, 2015; Kalleber & Dunn, 2016). When looking at the decision of a gig worker to participate in gig work, it is mainly a classical economic trade-off between four factors: on the one hand the disadvantage of lacking insurance for damages resulting from accidents and limited access to social security, and on the one hand the advantage or relatively better short term wage and higher flexibility (see for example Witteman, 2017b; Cahuc, Carcillo & Zylberberg, 2014).

The food delivery industry in the Netherlands is an industry where the gig economy is dominantly present. In this industry, two kinds of gig work models are present. In the first one, as used by the food delivery companies Deliveroo and UberEATS, workers are independent contractors and experience the effects described above. This work model used is more or less similar to so-called freelance models in other non-gig industries, therefore the workers in this part of the industry will be called "freelancers". In the second model, used by companies Foodora and Thuisbezorgd, the workers are in a so-called "on-call min/max" contractual relationship with the platform, which means the worker is called upon when there is work. The contract guarantees access to social security in the form of sick pay and accident insurance and guarantees a minimum number of hours that can be worked. In contrast to the term "freelancers", the latter type of workers will be called "hired workers". On an industry level, two general work models are used, however, on a firm level the specific work conditions and agreements differ between firms, even if they offer the same general work model. To clarify this distinction, the work model used by a firm is called a "work arrangement". This thesis will focus on the workers' choice to work in one of the two work models.

In the literature on contingent work, which is a commonly used broad term for work in non-standard work arrangements, various insights can be found on the factors that are important or influential for work model preferences of the worker. Osnowitz (2010) identifies two different preferences regarding these trade-offs related to the different employment statuses. First, contingent workers have a different perspective on job security than conventional employees do (Osnowitz, 2010), which translates into a trade-off between different risks. A conventional employee seeks long term security and comfort in working for one firm, in which they can grow on a personal level and obtain specialized skills and thus make themselves valuable. A contingent worker, however, seeks security by being involved in many jobs; If one job is not working out as planned, another can compensate for it (Osnowitz, 2010). Muffels & Luijkx (2008) call this phenomenon flexicurity. Second, Osnowitz (2010) identifies the flexibility in time and space that is created when an employee gets involved in contingent work as an influential factor on the decision to become contingent worker.

Although freelancing is not new, insights from traditional freelancing work arrangements, like Osnowitz (2010), cannot be applied to the gig economy for two reasons. First, work arrangements in the gig economy differ from traditional freelancing ones on the efficiency of the division of work, which in the gig economy is increased by using algorithms to plan work. Second, in the gig economy the relationship between the worker and the platform is weaker than in traditional freelance employment. Due to these differences, conventional policies might not be sufficient to regulate the gig economy. It is therefore important to understand the gig workers and their perspective on work arrangements offered in the gig economy. Does the same dualism as described for traditional employment and freelancing exists in the gig economy? Or do gig workers have uniform preferences regarding flexibility, job security and social security? Such insights are needed to understand the applicability of traditional labour market theories to the gig economy and to regulate the gig economy effectively. A 'one-size-fits-all' regulation may simply not be applicable to the gig-economy due to the aforementioned differences and cause more harm than good. This leads to the following main question:

'How do preferences for flexibility, payment models, sick pay and accident insurance coverage differ between freelancers and hired workers in the gig economy?'

The trade-off made by workers when choosing a work model in the gig economy will be the central theme of this research, focussing on the Dutch food delivery industry. The latter is chosen because firms in the food delivery industry offer various levels of social security access, job security, payment models and flexibility, in both freelance and hired work models. This industry is not settled on one specific work model, and firms sometimes even change their work arrangement, which leads to uncertainty and anger among the workers (see for example: NU.nl, 2017, 2018a, 2018b; NOS.nl, 2017, 2018a, 2018b, 2018c; AD.nl, 2017; Witteman, 2017a). To answer the research question this study has performed a survey among workers of four Dutch food delivery firms with differing work arrangements. This survey is set up using discrete choice methods to understand the job preferences of gig workers accident insurance, sick pay, payment model and flexibility. In particular, the difference between freelance gig workers and hired gig workers will be investigated by comparing the preferences between the groups.

To investigate the job preferences of gig workers, the next chapter discusses the theoretical background of the gig economy. Chapter three considers the methods. In chapter four the results are presented. This is followed by the discussion of the results and a conclusion.

2. Theoretical background

Defining what the gig economy is, and what its boundaries are, is challenging, because of the broad use of the term throughout media sources and academic literature (Abraham et al., 2017). In this thesis, the term gig economy is used, but in other literature this phenomenon is sometimes called the sharing economy, platform economy, collaborating economy, access economy, freelance economy, 1099 economy, or on-demand economy (Aloisi, 2015; Kalleber & Dunn, 2016). This thesis will not go into detail on the differences and regards these terms to be synonymous. In line with the majority of the existing literature on the topic (Kuhn, 2016; Abraham et al., 2017; Aloisi, 2015; De Stefano, 2015; Lobel, 2017; Singer, 2014), I here define the gig economy as *a change in the labour market due to the connectivity provided by the internet, which allows for mediation on online platforms between firms or private individuals with a one-time service task, and workers willing to perform this task.*

In the Dutch food delivery industry, two work models can be found of which the first one is working as an independent contractor. This entails that the worker has founded a company at the chamber of commerce, with the worker as only employee (Posthumus & Wilthagen, 2010). The worker's firm is then hired by the platform to perform the task. Agreements on work conditions and for example benefits are organized via negotiations, in which the details of the work relation between the firm of the worker and the platform are settled (Posthumus & Wilthagen, 2010). In this work model, no rights are guaranteed by the law. This means that the worker must negotiate the salary, benefits et cetera. The workers of a platform working as independent contractor, leads to flexibility for both the platform and the worker. From the platform's perspective, the independent contractor work arrangements offer a scalable workforce on a pay-as-you-go basis (De Stefano, 2015). The gig economy tasks are often created by dividing up the tasks, that together formed one job previously, into smaller tasks that can be outsourced using the platforms (Aloisi, 2015; Friedman, 2014; Sundararajan, 2016).

On the side of the independent contractor worker, the worker can work whenever and wherever one wants. But this flexibility has led to a shift in risks from employer to employee, leading to the freelancers sometimes bearing the risks for unemployment, sickness and occupational disability (De Stefano, 2015). According to Friedman (2014), the gig economy has led to "no more connection between the worker and the employer than there might be between a consumer and a particular brand of soap or potato chips" (p. 171).

The second work model is the on-call min/max labour contract. This is a labour contract that offers the worker job and income security in the form of a guaranteed number of minimal hours that can be worked

(FNV, n.d.). The worker is obligated to come when the employer calls for him/her, and there is an agreed number of maximum hours the worker can be called upon by the employer. Additionally, labour rights like sick pay, protection from on the spot firing of the worker, and accident insurance is covered by this form of contract, because of the legal employment status of the worker as an employee of the platform (FNV, n.d.).

Research into work models and labour conditions teaches us that there are two fundamental differences between these work arrangements. These differences are not unique for the gig economy, they originate from the structure of the work arrangements, which are also used outside the gig economy. First, dependent employees and, consequently, hired workers in the gig economy, have a certain level of job and income security (Van der Torre, Dirven & Van de Ven, 2018), due to the guaranteed minimum amount of work a worker gets offered each week. Hired workers are also protected via dismissal laws from on-the-spot firing. The rights of hired workers are guaranteed by law, and therefore are not unique for the gig economy. Working in an independent contractor model, however, does not provide these certainties. In negotiations between the platform and the worker, these attributes could be settled, but they are not standard or ordered by law.

The second difference between the models as they are used in the gig economy is the social security benefits (Etzioni, 2018; Shevchuk, Strebkov & Davis, 2018; Green et al., 2018; Gross, Musgrave & Janciute, 2018; Malos, Lester & Virick, 2018; Snider, 2018). In line with the job and income security, access to social security is organized through the law for hired workers and is negotiable for freelancers. Important side note is that the hired workers do not have parental leave or pensions, only sick pay and work-related accident insurance is required by law. The four main independent variables used in answering the main question are derived from these themes: sick pay and accident insurance are related to social security; payment model and flexibility are related to income and job security.

2.1 Sick pay

The first independent variable is sick pay. Sick pay entails the platform paying the worker while he/she is unable to work. In the Netherlands, an employer needs to pay the sick employee for almost two years if he/she has a full employment contract. Generally, social security benefits are positively valued (George, 2018). Therefore, the general hypothesis can be formulated:

H1a: All gig workers prefer work arrangements including sick pay over work arrangements without sick pay.

In the on-call min/max contracts offered by the platforms, the duration of sick pay being provided by the platform can be shortened. However, through regulation, sick pay is guaranteed to hired workers. Freelancers on the other hand, do not have access to this social security if they have not negotiated it in their labour contract. Workers in the gig economy being hired by a platform as independent contractors often leads to the platform having fewer responsibilities regarding the workers' wellbeing, because of it not being negotiated upfront (Aguirre et al., 2018; Gross, Musgrave & Janciute, 2018; Zwick, 2018). This construct leads to freelancers having less access to social securities (De Stefano, 2015; Abraham et al., 2017; Malos, Lester & Virick, 2018).

To construct a hypothesis from these insights, it is assumed that workers actively choose one platform over the other because the workers prefer the set of labour conditions offered by this platform. This means that it is expected that workers self-select to a work arrangement that best fits their preferences. This leads us to form the hypothesis:

H1b: Hired workers have a stronger preference for work arrangements including sick pay than freelancers.

2.2 Accident insurance

Another responsibility regarding the wellbeing of the freelancer that in the gig economy is shifted from the employer to the worker through the independent contractor scheme is the accident insurance (Green et al., 2018; Aguirre et al., 2018; Malos, Lester & Virick, 2018; Zwick, 2018). Accident insurance coverage entails that the platform covers the costs of damages to the rider, and the rider's bike, when an accident occurs during worktime. In general, accident insurance coverage is expected to be regarded as positive (Monazzam & Soltanzadeh, 2009). Therefore, the following hypothesis is formulated:

H2a: All gig workers prefer work arrangements including accident insurance coverage over work arrangements without accident insurance coverage.

The freelancer as independent contractor has multiple options; they could negotiate the accident insurance in their labour contract, or they could organize this themselves by setting aside some of the wages to have a financial buffer, or they could accept the risk and earn more money (Finkj & Nagl, 2018). Currently, there is no option for freelancers to insure themselves for these costs at big insurance firms. Hired workers on the other hand are insured by the platform, as is regulated by law. Using the same argumentation as presented at hypothesis H1b, we arrive at the hypothesis:

H2b: Hired workers have a stronger preference for work arrangements including accident insurance coverage than freelancers.

2.3 Flexibility

The third factor to consider in the trade-off when choosing freelance gig work over hired gig work is the increased flexibility that freelance gig work offers (see Burtch, Carnahan & Greenwood, 2018; Green et al., 2018; Lehdonvirta, 2018; Marquis et al., 2018; Wood, Graham, Lehdonvirta & Hjorth, 2018, Van der Torre, Dirven & Van de Ven, 2018). Flexibility means freelancers have the possibility to choose when and where they would like to work (Lehdonvirta, 2018). Generally, it could be expected that gig workers prefer flexibility and therefore working without scheduled working times (Ciarniene & Vienazindiene, 2018). The following hypothesis is formulated as a result:

H3a: All gig workers prefer work arrangements without scheduled worktime over work arrangements with scheduled worktime.

Two methods of work allocation are present in the food delivery industry for the rider to work, which offer different levels of flexibility. Firstly, drivers can assign themselves to slots in a schedule. Riders are then expected to work on the time they scheduled. Also, these timeslots can fill up, so there is a maximum of riders that can plan their work in advance (Van Boven, 2017). Additionally, a second method exists, in which the driver simply hits a button on their app to notify the platform that he/she wants to work (Van Boven, 2017). The flexibility offered in this model creates the opportunity for workers to combine the gig work with activities that are less predictable, like family care (Harris and Krueger, 2015; Kalleber & Dunn, 2016). Using the argumentation from hypothesis H1b, this leads us to form to the following hypothesis:

H3b: Hired workers have a stronger preference for work arrangements including scheduled worktime than freelancers.

2.4 Payment model

To specify the potential wage increase of freelance workers in the gig economy in comparison to hired workers, it is important to discuss the difference in payment models between hired workers and freelancers (see Green et al., 2018; Gross, Musgrave & Janciute, 2018). There are two models: payment per hour, and payment per delivery (Van Boven, 2017; Witteman, 2017b; Deliveroo, n.d.). In general, it is expected that more income security in the form of per hour payment is preferred over the riskier per delivery model. This leads us to form to the following hypothesis:

H4a: All gig workers prefer work arrangements in which the worker is payed per hour over work arrangements in which the worker is payed per delivery.

The important mechanism is that a food deliverer in the gig economy could potentially make more money by being paid per delivery, than when being paid per hour, due to the uncertainty about the length of rides (Graham, Hjorth & Lehdonvirta, 2017). However, the limiting factor is the timespan in which the deliveries can be done, which is about three hours at the start of the evening. Therefore, there is a certain potential for earning more than hired workers, but this also creates more risks; after all, if there are no tasks, a freelancer cannot make money. Using the argumentation from hypothesis H1b, we arrive at the following hypothesis:

H4b: Hired workers have a stronger preference for work arrangements in which the worker is payed per hour than freelancers.

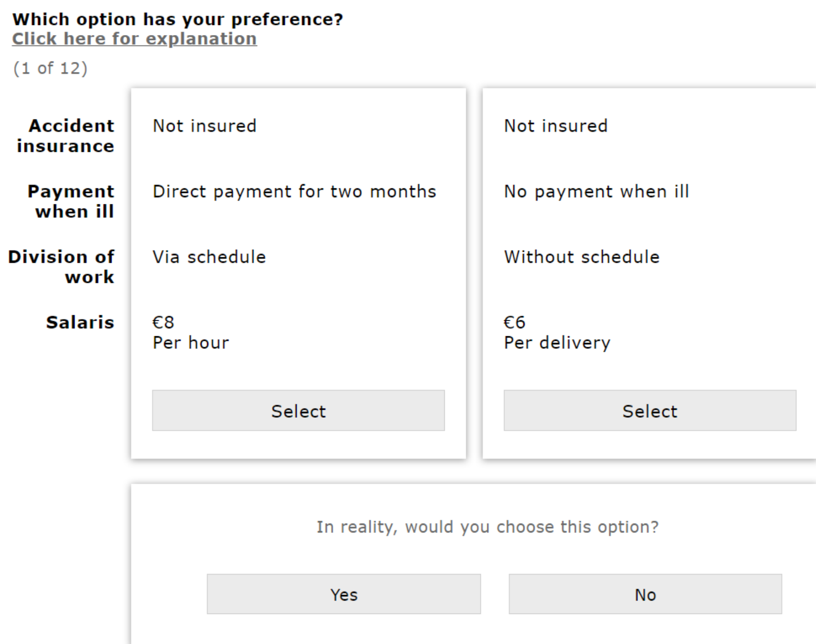
3. Methods

3.1 Research design

This research has a quantitative deductive approach, namely a discrete choice experiment (DCE; see Ryan, Gerard & Amaya-Amaya, 2008; Bliemer & Rose, 2016). Discrete choice experiments are developed in transportation studies, where optimisation of transport processes is the focus. The method is also useful in market research, to compare products and their characteristics and optimise the attributes of the product. Discrete choice experiments entail that for each independent variable, and in this research two control variables, attribute levels are created. Attribute levels are fixed values or options that are linked to the variable, like accident insurance coverage having the attribute levels 'insured' and 'not insured'. From the set of attribute levels two scenarios are created (see figure 1). In a scenario, six attribute levels, one of each of the variables, are included. This scenario represents a work arrangement, and by comparing the two scenarios that are presented, the respondent can compare the aspects of the work arrangements. By choosing one of them, the respondent signals its preference for the set of attribute levels that are included in that instance in comparison to the other alternative's set of attribute levels. Accordingly, the unit of analysis of the research is the respondent's preference for one specific work arrangement over another one.

This data is supplemented with data on control variables on the level of the respondent, like age. Using this data in the models will add context and realism to the results, which leads to conclusions that are better applicable to reality. Using three conditional logit regression models makes it possible to shed light on the aforementioned hypotheses and, as a result, answer the main question.

Figure 1: A choice as it was presented in the DCE survey



3.2 Dependent and independent variables

For the DCE, the attributes that make up the choice and their possible levels should be identified (Ryan, Gerard & Amaya-Amaya, 2008). The attributes of the choice are four concepts, which are operationalized in table 2. In the final survey, six concepts were formulated questions for, these are the four core concepts and two control variables (see 3.3). Offering realistic options to the respondents is key in DCE's. By constructing the scenarios from attribute levels that are found in practice, the level of realism in the scenarios is high.

The dependent variable is the choice of the respondent for one of the alternatives presented to him/her. In the data, a choice consists of a vector of the attribute levels of the alternative that is chosen by the respondent (see 3.7). These attribute levels are compared to the attribute levels that were not chosen. The alternatives constructed are from the attribute levels of the independent variables.

Table 1: Operationalisation of dependent variable

Dependent Variable	Kind of variable	Measure
Choice	Attribute level	0 = option is not chosen by respondent 1 = option is chosen by respondent

The first independent variable is accident insurance coverage. Accident insurance coverage means that the rider is insured for damage caused by an accident. For example, damages to the rider's bike. Deliveroo, Thuisbezorgd.nl and Foodora offer insurance to their workers (Witteman, 2017b). Currently, there is no option for freelancers to insure themselves for these costs. UberEATS riders, therefore, do not have an insurance (Witteman, 2017b). The attribute levels are operationalized as 'insured' and 'not insured' and are coded as 1 and 0 (see table 2).

The second independent variable is sick pay. Sick pay is the substitute for salary a worker gets when he/she is unable to work due to sickness. Thuisbezorgd offers sick pay for a length of seven days, Foodora offers sick pay for 60 days. UberEATS and Deliveroo do not offer sick pay (Witteman, 2017b). Sick pay is operationalized in four options: no payment, one week, one month or two months. The one-month option is added to decrease the difference between the levels. The variable is operationalized as either 0 days of sick pay, 7 days, 30 days or 60 days (see table 2).

The third independent variable is flexibility. With flexibility the study refers to the possibility of the worker choosing when and where to work. All platforms offer the option for riders to plan their work hours in a schedule. Subscribing to a timeslot is binding, the worker is expected to work on that time. This method is used by all platforms. However, Deliveroo and UberEATS include an option in which no schedule is used. The rider can choose to work without upfront notice. For operationalisation two attribute levels are used: first, 'via schedules' (coded as 1), the second 'without schedule' (coded as 0; see table 2).

The fourth independent variable is the payment model. Two payment models are used in the industry: per hour payment, which means the rider is paid a certain salary per hour independent of the amount of deliveries the rider completes that hour. The second method is payment per delivery, which entails being paid per ride. This entails more risk, because if there are no food orders, the worker cannot make a living. The first payment model is used by Thuisbezorgd and Foodora, the second is used by Deliveroo and UberEATS. Payment model has two attribute levels: 'per delivery' which is coded as '1', and 'per hour', which is coded '0' (see table 2).

Table 2: Operationalisation of independent variables

Independent Variable	Kind of variable	Measure
Accident insurance	Attribute level	0 = not insured 1 = insured
Sick pay	Attribute level	Continuous scale of values between 0 and 60 days
Flexibility	Attribute level	0 = without schedule 1 = via schedule
Payment model	Attribute level	0 = payment per hour 1 = payment per delivery

To be able to compute the differences between freelancing and hired gig workers' preferences, it is tested which work arrangement the worker is currently involved in. This variable is called work model. This is measured by asking how many hours the respondent has worked for four Dutch food delivery platforms. The platforms are divided between platforms that use an independent contractor work model, UberEATS and Deliveroo, and firms that work with a hired work model, Thuisbezorgd.nl and Foodora. It is of course possible for a person to work for multiple firms, in that case the platform the respondent works most hours is used in the analysis (see table 3).

Table 3: Operationalisation of work model variable

Variable	Kind of variable	Measure
Work model	Individual level	0 = respondent is a hired worker 1 = respondent is a freelancer

3.3 Control variables

Additionally, several control variables are measured. Including the control variables will be useful to check if the results are really caused by the main independent variables rather than a control variable. By adding the control variables, the influence of the independent variables is embedded within the more general data context. This increases the applicability of the model and can therefore be used to check the results of the other models. The operationalisation of the control variable is presented in table 4. The following control variables are included:

- ***The respondents age***, which is included as it is expected to be relevant for effects of age on the risk awareness of people and the necessity of a stable income. The age variable is operationalised as a continuous variable of only discrete numbers.

- ***The time the respondent spent on answering the questions***, which is included because of the data gathering strategy. Riders often fill out the survey in their breaks, therefore haste could be of influence on the choices they make. Extreme cases (one respondent did not close the survey tab for more than 300 hours) were taken out. It is assumed that at maximum, a respondent spends 20 minutes on the questions, which is therefore used as cut-off point. If the time spend on the survey is higher, the data is not included (see 4.1).
- ***The respondents' highest educational level***. This is important to control for, because the kind of jobs people of different educational backgrounds can do differs. This means that the environment which the work arrangements are compared to is different between educational levels. The variable is scaled using Schröder & Ganzeboom (2012), who presents a scale to compare Dutch educational levels based on the percentage of Europeans that have completed the educational level. For example, elementary school is completed by most people, this means this is a low educational level. Fewer people have finished a bachelor's degree at university, so this is a higher educational level.
- ***Hours worked per month for the platform*** indicates the time spend on the job, risk preferences could be influenced by this. For example, a rider who works 100 hours per month has more exposure to dangers in traffic than a worker who only works 10 hours. Therefore the 100-hour worker is possibly more likely to prefer accident insurance coverage. Additionally, one could argue that sick pay is more relevant when the rider works more, because working a lot as rider means that a bigger share of your total income is dependent on the delivery work. This means this worker being sick has more impact on the worker's income than for a worker working less hours.
- ***Delay of sick pay starting day.*** In the sick pay models of the platforms, a difference in approach is noticeable. Where Thuisbezorgd pays sick pay directly when a rider calls in sick, Foodora only provides sick pay after two days. Probably, the reasoning behind this is that generally people are sick for less than two days. This difference could have an influence on the attractiveness of sick pay as an attribute of the work arrangement, therefore the delay of the sick pay starting date is considered as control variable.
- ***Nationality of the respondent***. This is measured through the language of the survey. The respondents had the choice to fill it out in Dutch or in English. This is used as a proxy for the nationality of the respondent. In other countries, other labour laws are applicable. The norm in the Netherlands could be different in other countries. This means that people with a different nationality may have a different preference: Dutch may be less risk loving because they are used

to high employment standards, whereas this may not be the case for other nationalities. This could influence the choices respondents make.

- ***Expected deliveries per hour***. The amount of deliveries per hour a rider expects to make influences the trade-off between payment models, after all if you deliver more deliveries per hour, the per delivery payment structure becomes more appealing, because there is more potential to earn money
- ***The income level***, which entails the amount of money earned in the work arrangement influences people's attitude towards the other attributes. For example, one would not want to ride uninsured for €3 per delivery, but with a pay of €6 per delivery, the insurance could otherwise be organized. This would mean that the necessity of insurance through the platform would decrease. Additionally, classic economics teaches us that higher wages are more attractive than lower wages, therefore this could influence the outcomes.

Table 4: Operationalization of control variables

Variable	**Operationalization**	**Measure**
Age	Years since birth	Continuous
Survey completion time	Time spend on question pages of survey. Maximum of 20 minutes.	Continuous
Hours worked	Total hours worked in the past month	Continuous
Educational level	Level of highest finished education, scaled using the ISLED scale of Schröder &Ganzeboom (2012)	0.258 = elementary school 0.541 = high school 0.530 = practical education (MBO) 0.612 = university of applied sciences (HBO) 0.841 = university bachelor 0.878 = university master NA = other
Mode of transport	Transportation mode	1 = bike 2 = electric bike 3 = moped
Income level		1 = low wage (€3 per delivery or €8 per hour) 2 = medium/low (€4 per delivery or €10 per hour) 3 = medium/high (€5 per delivery or €12 per hour) 4 = high wage (€6 per delivery or €14 per hour)
Delay of sick pay	Days of delay before sick pay starts	0 = direct payment 2 = two days delay before payment When duration is 0, delay is NA
Nationality	Language of survey	0 = Dutch language 1 = English language
Deliveries per hour	Amount of deliveries made in an hour	Continuous

Importantly, the control variables are integrated in the model as an interaction between the control variable and an independent variable. The control variables therefore do not control directly for the influence of the control variable on the choice but do so indirectly by measuring the influence of the control variable on an independent variable, which then influences the dependent variable. In short, this is done because the conditional logistic regression that is used, can only calculate differences between choices. A control variable like age is not different between two choices, but only between respondents. However, when the control variable, which is on the level of the individual, is multiplied by a variable that differs on the level of the choice, the computed variable also possesses this characteristic, and is therefore useful in the analysis (for more detail, see section 3.5). Including all interactions between control variables and independent variables would lead to a model with 30 variables, which is undesirable because of overfitting concerns and degrees of freedom problems. Therefore, a selection had to be made which control variables are relevant in relation to an attribute level (see table 3).

Table 5: Selection of control variables as interaction terms

	Age	**Survey completion**	**Hours worked**	**Educational level**	**Nationality**	**Deliveries per hour**
Accident insurance	x	x	x	x	x	
Sick pay	x	x	x		x	
Flexibility	x	x		x	x	
Payment model	x	x	x		x	x

The continuous control variables were centred by subtracting the mean of the variable of each of the individual variables. This means that after centring, the variable has an average of 0. When variables are not centred, the coefficients of other variables in the model that is presented is based on the non-centred variable having value 0, which often is not very insightful. For example, one does not need to know what the sick pay preference is of a 0-year-old rider. By centring, this problem is overcome. Because the average of the centred variable is 0, the coefficients of the other variables in the model are based on the average of the centred variable. This leads to more insightful results. The variables that are centred are age, hours worked, educational level, survey completion time and deliveries per hour.

3.4 Data collection

Data was collected via a questionnaire with closed questions among the workers of the four Dutch food delivery firms. The full questionnaire can be found in appendix 1. First, the respondents entered information on the individual level control variables. Second, the respondents answered a question related to the current work arrangement. The respondents were asked how many hours they have worked for each of the firms in the past month.

Lastly, the most important element was the choice scenarios, which was presented in pairs (see figure 2). The respondents appointed their preference to one of the scenarios, which provided insight in their trade-off. The choice made by the respondent is the dependent variable used in the analysis. For the construction and distribution of the questionnaire, Sawtooth Software, a survey tool, was used.

The software package used, Lighthouse studio, a part of Sawtooth Software, allows the attribute levels to be randomized in the scenarios. The software calculated 200 random surveys. If these surveys were to be filled out, the distribution of the surveys would be so that each attribute level was tested as much as the others of that attribute. Twelve scenarios were presented to each of the respondents. In a scenario, two options were shown. The respondent then selected the one they preferred. Next, the respondent was asked if he/she thinks they would have chosen the option in reality. This was important to verify the realism of the answers given by the respondents. If a comparison between options is considered to be unrealistic, it is not included in the analysis.

The survey was held among the workers of the four dominant firms in the food delivery industry. A convenience sampling strategy was used (see Bryman, 2015), to construct a sample of the workers of these firms. The respondents were approached by following them by bike and when they were standing still for a moment asking them to fill out the survey. If they said they did not have time for this, a card with the website link to the survey was given. This way, usable responses from overall 102 respondents were collected, leading to N = 936.

3.5 Data analysis

A conditional logit model is used to test the hypothesis. The conditional logit model was developed by McFadden in 1973 and is often used in transportation studies (Hoffman & Duncan, 1988). Conditional logit regression is a model that is suited for modelling of polychotomous choice situations (Hoffman & Duncan, 1988). The model can be used to compare alternatives within a choice and uses the characteristics of the choice and not the characteristics of the individual to estimate the coefficients (Hoffman & Duncan, 1988).

Two kinds of variables are used in this model. First, attribute level variables. These are variables that are presented in the choice and are compared to each other. The alternatives that are presented (the set of attributes) differ for each question. The second kind of variable are variables that stay the same for each choice, for example the age of the respondent. These are called individual level variables. In a conditional logit model only attribute level variables can be tested.

When individual level variables are added, this variable will not change the alternatives presented to the respondent. The model aims to find differences between alternatives and compare the preferences. The fact that the individual level variable does not change means there is no outcome. Unfortunately, this leads to no data on the influence of the control variable on the independent variable. There are two possible solutions for this. First, one could use a mixed model approach, in which the individual level variables are tested in a multinomial regression and the attribute level variables are measured in a conditional logit regression (see Hoffman & Duncan, 1988). Second, one could transform the individual level variables to attribute level variables by multiplying the individual level variable with an attribute level variable. For example, if a respondent is 20 years old, and in their first question chooses an accident insurance level of 1, and in its second question chooses an accident insurance level of 0, the age and accident insurance interaction variable would have the values of 20 * 1 = 20 in the first question, and 20 * 0 = 0 in the second question. This way a variable on the individual level (like age), is transformed into a variable which values differ between choices made by the respondent; an attribute level variable. The latter option is chosen, because all individual level variables that are added are control variables. It is unnecessary to know the direct influence of control variables on the choice, after all, they are not necessary to test the hypotheses.

Because of the individual level variables all being control variables, this was not compromising the usability of the data. After all, for the measuring of the hypotheses, sometimes direct effects were necessary, which could not be measured when using the individual level variables. However, for control variables these direct effects were not essential.

The transformation of variables and the calculation of the model estimates were done using R. The R-script that was used is included in appendix 2.

3.7 Model structure

To test the hypotheses, three models were computed. In the first model (model A), only the main independent variables (sick pay, accident insurance, flexibility and payment model) were included, as direct effects. The results of this model are used to test hypothesis 1a, 2a, 3a and 4a. The second model (model B) includes the main independent variables as direct effects and by adding the work model variable as an interaction term with the main independent variables is aimed at investigating the differences between hired workers and freelancers. This model is used to test hypothesis 1b, 2b, 3b, and 4b. The last model (model C) also includes the control variables, which are entered as interaction terms (see section 3.1). Model C is computed to investigate if the results still hold when the model is made more realistic by adding control variables. The models are visualized in figure 2.

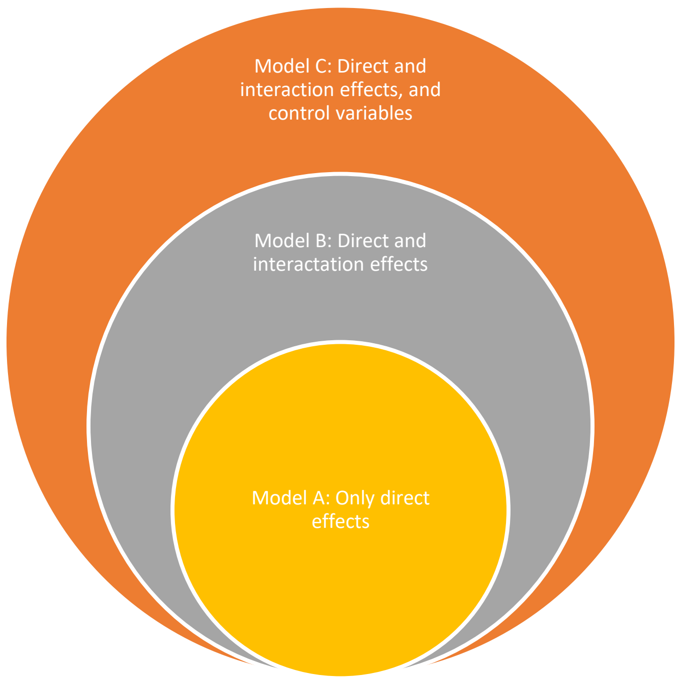


Figure 2: Visualization of variables used in model

The general equation (1) for conditional logistical regression is

$$P_{ij} = \frac{\exp(\boldsymbol{X}_{ij}^{T} * \boldsymbol{\beta})}{\sum_{k=1}^{J} \exp(\boldsymbol{X}_{ik}^{T} * \boldsymbol{\beta})} \quad (1)$$

Where:
P_{ij} = probability that an individual i chooses alternative j.
X_{ij} = vector of characteristics of the jth alternative chosen by individual i.
β = the parameter vector of the jth alternative of the individual i.
X_{ik} = characteristics of the alternatives.
J = the number of alternatives.

Accordingly, model A can be expressed with the following mathematical equation (2) as

$$P_{ij} = \frac{\exp(\beta_1 * X_{ij\,1} + \beta_2 * X_{ij\,2} + \beta_3 * X_{ij\,3} + \beta_4 * X_{ij\,4})}{\exp(\beta_1 * X_{1A} + \beta_2 * X_{2A} + \beta_3 * X_{3A} + \beta_4 * X_{4A}) + \exp(\beta_1 * X_{1B} + \beta_2 * X_{2B} + \beta_3 * X_{3B} + \beta_4 * X_{4B})} \quad (2)$$

Where:
P_{ij} = probability that an individual i chooses alternative j.
X_1 = attribute level of accident insurance chosen by individual.
β_1 = the coefficient of chosen accident insurance alternative
X_2 = attribute level of sick pay chosen by individual.
β_2= the coefficient of chosen sick pay alternative
X_3 = attribute level of flexibility chosen by individual.
β_3 = the coefficient of chosen flexibility alternative
X_4 = attribute level of payment method chosen by individual.
β_4 = the coefficient of chosen payment method alternative

X_{1A} = attribute level of accident insurance alternative A.
X_{2A} = attribute level of sick pay alternative A.
X_{3A} = attribute level of flexibility alternative A.
X_{4A} = attribute level of payment method alternative A.
X_{1B} = attribute level of accident insurance alternative B.
X_{2B} = attribute level of sick pay alternative B.
X_{3B} = attribute level of flexibility alternative B.
X_{4B} = attribute level of payment method alternative B.

β_1 = the coefficient of accident insurance alternative B.
β_2 = the coefficient of sick pay alternative B.
β_3 = the coefficient of flexibility alternative B.
β_4 = the coefficient of payment method alternative B.

Similar models can be made for model B and C. However, the formulas become lengthy very quick and are therefore not be presented here.

3.8 Research quality indicators

Regarding internal validity, the main pitfall of the research is the assumption that a worker has actively and knowledgably taken the decision to work in a certain work arrangement. This could of course not be the case, which would undermine the outcomes of the research. It is however assumed that although an average worker does not include all possible terms of employment in their decision-making process, one does compare possible jobs. By choosing one firm over another, they express their preference for a certain work arrangement over another.

Another important validity to discuss is the external validity. The generalisability of the research is not expected to be an issue. Because a respondent is confronted with twelve questions in which scenarios are weighted, filling out one survey leads to twelve data points. The research design therefore allows for finding significant results even with a relatively small sample.

4. Results

4.1 Descriptive statistics

In the data collection phase, 152 respondents filled out the survey at least partly. 102 respondents completed the survey, of which 69 are hired workers and 33 are freelancers. The data of these respondents is used for the analysis. The respondents filled out 12 questions, 288 scenario comparisons were found unrealistic by the respondents. Leading to N = 936.

In table 6, the categorical and interaction variables, and their respective values and occurrences are presented. In table 7, the minimum, quadrants, median, mean, maximum and number of NA's of the continuous variables is presented. There are no noteworthy observations.

Table 6: Values and occurrences of categorical variables (left table) and interaction variables (right table)

Variable	**Value**	**Occurrence**
Work model	0	630
	1	306
Sick pay	0	189
	7	245
	30	244
	60	258
Accident insurance	0	371
	1	565
Flexibility	0	455
	1	481
Payment model	0	673
	1	263
Income level	1	146
	2	209
	3	262
	4	319
Delay	0	369
	2	378
	NA	189

Variable			**Value**			
Work model x Sick pay			0	7	30	60
	Work model	0	129	164	171	166
		1	60	81	73	92
Work model x Accident insurance			0		1	
	Work model	0	250		380	
		1	121		185	
Work model x Flexibility			0		1	
	Work model	0	275		355	
		1	180		126	
Work model x Payment model			0		1	
	Work model	0	482		148	
		1	191		115	
Delay x Sick pay			0	7	30	60
	Delay	0	0	126	125	127
		2	0	119	119	131
		NA	189	0	0	0
Nationality x Sick pay			0	7	30	60
	Nationality	0	149	184	187	202
		1	40	61	57	56
Nationality x Payment model			0		1	
	Nationality	0	518		204	
		1	155		59	
Nationality x Flexibility			0		1	
	Nationality	0	344		378	
		1	111		103	
Nationality x Accident Insurance			0		1	
	Nationality	0	275		447	
		1	96		118	

Table 7: Minimum, quadrants, median, mean, maximum and number of NA's of the continuous variables.

Variable	Value	Min	1st quad	Median	Mean	3rd quad	Max	NA
Age x Sick pay	0	16	19	21	22.07	25	37	0
	7	16	19	21	22.64	25	58	0
	30	16	19	21	22.17	24.25	58	0
	60	16	19	21	22.12	25	37	0
Age x Accident Insurance	0	16	18	21	21.68	24	39	0
	1	16	19	21	22.64	25	58	0
Age x Flexibility	0	16	18	21	22.26	25	39	0
	1	16	19	21	22.26	25	58	0
Age x Payment model	0	16	19	21	22.16	25	58	0
	1	16	19	21	22.52	25	35	
Survey completion time x Sick pay	0	95	228	260	296.2	331	1003	26
	7	95	228	272	311.4	348	1003	20
	30	95	233	285	310.8	355.5	1003	22
	60	95	2330	275	318.5	351	1003	24
Survey completion time x Flexibility	0	95	228	274	311.5	349	1003	50
	1	95	231	275	309.1	351	1003	42
Survey completion time x Accident insurance	0	95	228	274.5	306.5	341	1003	37
	1	95	233	275	312.7	357	1003	55
Survey completion time x Payment model	0	95	228	272	304.7	341	1003	56
	1	95	233	286	325.4	366	1003	36
Hours worked x Sick pay	0	4	25	40	56.34	80	400	0
	7	5	25	40	60.68	80	400	0
	30	4	24	40	60.57	81.25	400	0
	60	5	21.75	40	64.28	80	400	0
Hours worked x Accident Insurance	0	4	20	37	58.4	80	400	0
	1	5	25	40	62.32	85	400	0
Hours worked x Payment model	0	4	28	40	61.44	80	400	0
	1	5	20.5	40	59.04	80	400	0
Education x Accident Insurance	0	0.258	0.541	0.541	0.5764	0.6120	0.878	13
	1	0.258	0.541	0.541	0.5874	0.612	0.878	12
Education x Flexibility	0	0.258	0.541	0.541	0.5837	0.612	0.8780	12
	1	0.258	0.0541	0.541	0.5825	0.6120	0.8780	13
Deliveries per hour x Sick pay	0	2	2	3	3.127	3	10	0
	7	2	3	3	3.168	3	10	0
	30	2	3	3	3.168	3	10	0
	60	2	3	3	3.178	3	10	0
Deliveries per hour x Payment model	0	2	3	3	3.183	3	10	0
	1	2	2	3	3.129	3	10	0

In table 8, the correlation matrix of the variables used in the models is presented. Some of the variables are used in the model as an interaction. These interactions are not included in the correlation matrix, because interactions have a strong correlation with the variables of which they are computed.

Table 8: Correlation matrix

	Sick pay	Accident insurance	Flexibility	Payment model	Age	Education	Survey completion time	Work model	Income level	Delay	Nationality	Hours worked	Deliveries per hour
Sick pay	1.000												
Accident insurance	0.044	1.000											
Flexibility	0.000	-0.029	1.000										
Payment model	0.025	0.004	-0.008	1.000									
Age	0.004	0.051	0.001	0.011	1.000								
Education	0.016	0.006	-0.003	0.004	0.597***	1.000							
Survey completion time	0.015	0.043	0.047	-0.001	0.250***	0.078**	1.000						
Work model	-0.007	0.010	-0.031	-0.008	0.082***	0.017***	0.158***	1.000					
Income level	-0.009	0.036	0.014	-0.016	-0.011	0.001	-0.006	0.001	1.000				
Delay	0.008	0.045	-0.017	-0.027	0.008	0.000	-0.008	0.002	-0.030	1.000			
Nationality	-0.004	0.001	-0.011	0.002	0.281***	0.288***	0.052***	0.019	0.009	0.014	1.000		
Hours worked	0.010	0.017	-0.020	-0.036	0.406***	0.409***	0.010	0.128***	-0.020	-0.025	0.149***	1.000	
Deliveries per hour	-0.007	-0.015	-0.021	-0.011	0.039	0.010	-0.101***	-0.121***	-0.024	0.004	-0.100	-0.119***	1.000

In the above correlation matrix, it is shown that most of the control variables (age, education, survey completion time, nationality, hours worked and deliveries per hour) do have a significant correlation. However, in the models, the control variables will be used as interaction. To check for multicollinearity between those variables, the variance inflation factor (vif) of each of the variables in the model was computed. The vif is a measure of the multicollinearity in between variables in a model, which uses the R^2 in the formula (3).

$$vif_i = \frac{1}{1 - R_i^2} \quad (3)$$

The vif is presented in table 9. The rule of thumb on interpretation of the vif is that if this value is higher than four, the variable is too correlated and should be removed. None of the variables has a vif higher than 4, therefore, there we can conclude that there is no problematic multicollinearity in the model.

Table 9: Variance influence factors of the models' variables

Explanatory Variables	Model A	Model B	Model C
Sick pay	1.024	1.744	2.355
Accident insurance	1.038	1.678	2.718
Flexibility	1.000	1.643	2.590
Payment model	1.061	1.872	3.393
Work model x Sick pay		1.694	1.995
Work model x Accident insurance		1.648	2.097
Work model x Flexibility		1.646	1.978
Work model x Payment model		1.782	2.257
Age x Sick pay			1.242
Age x Accident Insurance			1.768
Age x Flexibility			1.661
Age x Payment model			1.314
Survey completion time x Sick pay			1.354
Survey completion time x Flexibility			1.414
Survey completion time x Accident insurance			1.693
Survey completion time x Payment model			1.193
Hours worked x Sick pay			1.254
Hours worked x Accident Insurance			1.457
Hours worked x Payment model			1.300
Education x Accident Insurance			1.894
Education x Flexibility			1.724
Income level			1.293
Delay			1.088
Nationality x Sick pay			1.387
Nationality x Payment model			1.563
Nationality x Flexibility			1.529
Nationality x Accident Insurance			1.622
Deliveries per hour x Sick pay			1.305
Deliveries per hour x Payment model			1.269

4.2 Results of models

Three models were computed (see 3.7). Model A includes only the main independent variables, model B contains the main independent variables, and the independent variable and work model variable as interaction terms, and lastly, model C also includes the control variables. In table 10, the models' results are presented. From model A to C, by adding variables, the R-square increases from 0.132 to 0.208 meaning that with the highest model performance, only 20.8% of the variance is accounted for by the model predictors. This means there is still 79.2% of variance unaccounted for by the variables, which leaves room for further research in which additional variables should be considered (see 5.6).

Table 10: Results of the conditional logit regression. The coefficient is presented without brackets, the significance is presented in stars (see bottom of table for legend) and the standard error is presented between the brackets.

Explanatory Variables	Model A	Model B	Model C
Sick pay	0.010*** (0.002)	0.011*** (0.003)	0.010 (0.007)
Accident insurance	0.609*** (0.090)	0.629*** (0.417)	1.219*** (0.255)
Flexibility	0.054 (0.090)	0.417*** (0.120)	0.996 *** (0.254)
Payment model	-1.137*** (0.086)	-1.480*** (0.118)	-2.044*** (0.380)
Work model x Sick pay		-0.002 (0.005)	-0.002 (0.009)
Work model x Accident insurance		-0.018 (0.191)	-0.547 (0.120)
Work model x Flexibility		-0.948*** (0.194)	-1.418*** (0.369)
Work model x Payment model		0.843*** (0.182)	1.652*** (0.330)
Age x Sick pay			-0.001 (0.001)
Age x Accident Insurance			0.066 (0.043)
Age x Flexibility			0.011 (0.043)
Age x Payment model			0.019 (0.032)
Survey completion time x Sick pay			0.000 (0.000)
Survey completion time x Flexibility			-0.002 (0.001)
Survey completion time x Accident insurance			-0.001 (0.001)
Survey completion time x Payment model			0.001 (0.001)
Hours worked x Sick pay			0.000 (0.000)
Hours worked x Accident Insurance			0.001 (0.003)
Hours worked x Payment model			0.000 (0.003)
Education x Accident Insurance			1.731 (1.401)
Education x Flexibility			2.281* (1.417)

Income level			0.684*** (0.097)
Delay			-0.181* (0.091)
Nationality x Sick pay			-0.005 (0.011)
Nationality x Payment model			0.081 (0.370)
Nationality x Flexibility			-0.968* (0.403)
Nationality x Accident Insurance			-0.973* (0.410)
Deliveries per hour x Sick pay			0.006 (0.006)
Deliveries per hour x Payment model			-0.413* (0.193)
N	936	936	936
Concordance	0.718	0.739	0.824
R-square	0.132	0.154	0.208
Likelihood ratio test	264.9	313	292.5
Df	4	8	29
Wald test	197.4	213.9	121.7

Conditional logit estimation. Dependent variable: Choice of respondent. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In model A, hypotheses 1a, 2a, 3a and 4a can be tested (see table 11). From the sick pay coefficient, it can be concluded that the respondents prefer sick pay for longer periods over sick pay for shorter periods ($\beta = 0.010$, $p < 0.001$). Hypothesis 1a: *All gig workers prefer work arrangements including sick pay over work arrangements without sick pay*, can therefore not be rejected. With the accident insurance variable, Hypothesis 2a: *All gig workers prefer work arrangements including accident insurance coverage over work arrangements without accident insurance coverage*, can be tested. It shows that the respondents prefer being insured over not having an insurance ($\beta = 0.609$, $p < 0.001$). The flexibility variable, however, is not significant ($\beta = 0.054$, $p > 0.05$). This means that it does not play a role in choice for a certain work arrangement when looking at all respondents. The third hypothesis: *all gig workers prefer work arrangements without scheduled worktime over work arrangements without scheduled worktime*, can therefore be rejected. Fourth, the hypothesis '*All gig workers prefer work arrangements in which the worker is payed per hour over work arrangements in which the worker is payed per delivery*', cannot be rejected, due to the negative direction of the coefficient ($\beta = -1.137$, $p < 0.001$), which means respondents like to be payed per hour more so than if they were being payed per delivery.

Table 11: Hypotheses 1a, 2a, 3a and 4a

H1a	All gig workers prefer work arrangements including sick pay over work arrangements without sick pay.	Not rejected
H2a	All gig workers prefer work arrangements including accident insurance coverage over work arrangements without accident insurance coverage.	Not rejected
H3a	All gig workers prefer work arrangements without scheduled worktime over work arrangements with scheduled worktime.	Rejected
H4a	All gig workers prefer work arrangements in which the worker is payed per hour over work arrangements in which the worker is payed per delivery.	Not rejected

In model B, the interaction effects between the work model variable and the main independent variables are added (see table 10 and 12). From this model one could conclude that preference for sick pay length does not differ between hired and freelance workers. This can be seen from the work model x sick pay coefficient ($\beta = 0.002$, $p > 0.05$). Hypothesis 1b, *hired workers have a stronger preference for work arrangements including sick pay than freelancers*, can therefore be rejected. Both hired and freelancing workers prefer longer sick pay durations over shorter.

Moreover, there is no significant difference between hired and freelance workers regarding accident insurance preferences. This can be seen in the significance of the work model x accident insurance variable ($\beta = -0.018$, $p > 0.05$). Hypothesis 2b, *hired workers have a stronger preference for work arrangements including accident insurance coverage than freelancers*, can therefore be rejected. There is no difference in preference towards accident insurance between freelancers and hired workers.

However, regarding the flexibility freelancers have a significantly different preference towards flexibility, freelancers prefer working without schedule more than working with a schedule ($\beta = -0.948$, $p < 0.001$). This means that hypothesis 3b: *Hired workers have a stronger preference for work arrangements including scheduled worktime than freelancers*, could not be rejected.

Additionally, regarding the payment model, the coefficient of the direct effect is negative ($\beta = -1.148$, $p < 0.001$), and the interaction term coefficient is positive ($\beta = 0.843$, $p < 0.001$). This means hired and freelancers prefer being payed per hour over being paid per delivery, but freelancers have a less negative attitude towards payment per delivery. This means hypothesis 4b: *hired workers have a stronger* *preference for work arrangements in which the worker is payed per hour than freelancers*, cannot be rejected. Hired workers do indeed prefer being paid per hour more than freelancers.

Table 12: Hypotheses 1b, 2b, 3b and 4b

H1b	Hired workers have a stronger preference for work arrangements including sick pay than freelancers	Rejected
H2b	Hired workers have a stronger preference for work arrangements including accident insurance coverage than freelancers.	Rejected
H3b	Hired workers have a stronger preference for work arrangements including scheduled worktime than freelancers	Not rejected
H4b	Hired workers have a stronger preference for work arrangements in which the worker is payed per hour than freelancers.	Not rejected

In model C, the control variables were added to the direct and interaction effects (see table 10). As could be expected, the income level variable is significant ($\beta = 0.684$, $p < 0.001$), which means that respondents choose work arrangements with higher pay over work arrangements with lower pay. This also means that, the choice for a work arrangement is not only dependent on the four main independent variables researched in this thesis but is also dependent on the income level that accompanies the arrangement. Nevertheless, the accident insurance ($\beta = 1.219$, $p < 0.001$), flexibility ($\beta = 0.996$, $p < 0.001$)and payment model ($\beta = -2.044$, $p < 0.001$) variables remain statistically significant, so they are still relevant for the decision making of the respondent.

However, the sick pay loses its significance ($\beta = 0.010$, $p > 0.05$), which means that it has no influence on the respondent's choice that could not be explained by coincidence. The outcome of model A and B, in which it is found that sick pay is a relevant factor in deciding which work arrangement is preferable should therefore be used with caution. With regards to hypothesis H1a, the finding that it should not be rejected does not hold when the control variables are added. Therefore, further research into this is needed.

Additionally, the model C results show that a respondent who has had higher education, prefers working using a schedule more than a lower educated respondent (education x flexibility variable, $\beta = 2.281$, $p < 0.05$). Also, work models in which the sick pay is delayed are less preferred by the respondents than work models in which sick pay is directly provided (delay variable, $\beta = -0.181$, $p < 0.05$). Additionally, respondents that filled out the survey in English prefer working without schedule more than respondents that filled out the survey in Dutch (nationality x flexibility variable, $\beta = -0.968$, $p < 0.05$). They also don't mind not being insured compared to respondents who filled out the survey in Dutch (nationality x accident insurance variable, $\beta = -0.973$, $p < 0.05$). Lastly, respondents that expect to deliver more deliveries per hour prefer being payed per delivery more than respondents that expect to deliver less deliveries per hour (deliveries per hour x payment model variable, $\beta = -0.413$, $p < 0.05$).

5. Discussion

5.1 General interpretation of results

In this thesis I set out to research the difference in preference for aspects of work arrangements between people working in two different work models in the gig economy, being the freelancers working as independent contractor and the hired workers working on-call with a min/max contract. This research has found two important sets of results:

First, the result of testing hypothesis 1b and 2b, both hypotheses are rejected, show that freelancers do not differ from hired workers in their preference for social security in the form of sick pay and accident insurance coverage. Both groups prefer work arrangements with long sick pay and insurance coverage over arrangements with short or no sick pay and no insurance coverage. When the control variables are added, the sick pay variable lost its significance, which means that it does not influence the decision for a work arrangement. However, in models which only measured the main independent variables it was significant, so we may conclude that there is a relationship.

Second, the result of testing hypothesis 3b and 4b, which are both not rejected, show that freelancers do differ in preferences towards work arrangements when it comes to payment model and schedule usage. Freelancers prefer working on-demand, so without a schedule. Both freelancers and hired workers prefer being payed per hour, however, freelancers are less negative towards payment per delivery.

5.2 Scientific implications

From a scientific point of view, the research has added new empirical insights on the freelancer's preferences and attitudes to a limited literature base. When comparing the outcomes of this research to the findings of Osnowitz (2010), some interesting insights can be found. Firstly, Osnowitz found that job security has a different meaning for contingent workers than for employees. Where employees get their security from having a contractual relationship with the employer, contingent workers get security from having many clients. When looking at the results of this research, it can be seen that in the gig economy a different perception of security is present. Job security is measured through the preference for schedules and payment model. Freelancers prefer working without schedule, which is in line with Osnowitz' findings, but they prefer to be payed per hour, which is not something one would expect from Osnowitz' (2010) findings. Thus, based on these results one can conclude that on this matter the gig economy differs from the traditional economy.

The outcomes of this research support the findings of Osnowitz (2010) that flexibility is a driver for employers to choose contingent work. In this research it is shown that freelancers value flexibility more than hired workers. In this regard the conventional economy does not differ from the gig economy.

Additionally, by using discrete choice experiments, the value of this method for further social scientific research is shown. The method originating from market research proves applicable to social research and yield workable results.

5.3 Societal implications

Based on the findings in this research, it seems that the gig economy's new approach to work allocation resonates with workers. There appears to be a self-selection of workers, that choose to either work as freelancer or as hired worker, which is related to the work conditions of the work arrangements and the personal preferences of the workers. The lack of income security due to the platform's payment model and the lack of job security resulting from the scheduling practices, are accepted and sought for by freelancers. It is possible that behind this self-selection process, the difference in risk perception between workers is important. Possibly, a hired worker perceives the freelance work model as too high of a risk, whereas a freelancer is willing to accept this risk. However, this logic does not apply to all aspects of the work arrangements. From this study it became apparent that both freelancers and hired workers value social security in the form of sick pay and insurance coverage, however, these benefits are not offered by the platforms with a freelance work model. Thus, there is a discrepancy between the risk preferences of the freelancers and the work model. To put this in a broader perspective, in Sundararajan (2016) argues in 'the Sharing Economy' that in the conventional economy, firms and workers are in a relatively stable power equilibrium. However, by introducing the gig economy's independent contractor, the number of workers on the labour market has increased dramatically. The amount of work, however, did not increase in the same fashion. Sundararajan (2016) argues that classical economic theory teaches that if supply increases and demand is stable, prices drop. With the broadening of the labour market in which freelancers compete for tasks of the platforms, a race-to-the-bottom could occur, in which wages and labour conditions worsen.

Unique to the workers in the freelance model is that they compete not only with each other, but they also compete with workers from the hired work model. One could argue that this has contributed to Foodora quitting activities in the Netherlands. The freelance platforms can offer lower prices for delivery, and therefore are able to outcompete the hired work models. Building on this, one could argue that the current process of self-selection among workers is not sustainable. This would mean that if the hired workers would like to keep delivering food, the hired workers will be forced to start working in the freelancer model, which would be counter-preferential for them. This shift from a hired to freelance model is also appearing in other sectors, like cleaning and IT-jobs, where freelance models are emerging and competing with hired work models.

To prevent this situation where a race-to-the-bottom occurs. Policy makers are facing a choice between two solutions. First, the government could interfere in the market regulation by changing the freelancer's independent contractor status. Offering job, social and income security would have to be made attractive for platforms, and not offering them should be discouraged. However, this would negatively affect the possibilities the gig economy has to offer as a highly efficient way of mediating between workers and work. After all, firms associated with gig work platforms do thrive because of the lack of commitment between the freelancer and firm. Additionally, the freelancers have chosen to be in the freelance model, so regulating in a manner that forces them to a hired work model could perceived as overregulation or unduly market infringement. Policymakers should focus on regulating a basic system that ensures access to social security and that tries to uphold the flexibility and payment model at the same time.

A second option to achieve this, could be forcing the platforms to implement a social safety net through unionisation. A historical parallel can be found in the industrial revolution and with the creation of labour law. Organizing strikes and unifying in unions contributed to the founding of institutions like pensions, sick pay and labour contracts were implemented. Indeed, initiatives like this have occurred in the delivery sector as well, such as the Riders Union for independent contractors working for Deliveroo.

A combination of this top-down and bottom-up solution is probably most effective. On the one hand the freelancers could unify and demand less risky work conditions, on the other, policymakers could implement a clear minimal commitment of for the firms to the wellbeing of the workers. This would require significant negotiations, adjustments and adaptions from both parties to come to an optional situation that ensures employee wellbeing whilst embracing the efficiency of the new gig economy.

5.5 Limitations

One of the limitations of the research, and a key point of improvement for possible further research, is the low response rate of the survey. A few ideas come to mind for improving this in further research. Firstly, the number of questions asked in the survey should be decreased. The survey contained nineteen questions, requiring about ten minutes to fill out. Unfortunately, this has proven too long considering the data gathering strategy of following riders and asking them to fill out the survey in the small timespan between deliveries. It is possible that more riders would have been reached out to if the survey had taken five minutes. One way to achieve this would be to take out questions which yielded results not used for the research, like the amount of wage the rider will earn or the after which time the sick pay would start. Additionally, the amount of discrete choice questions could be scaled down to ten instead of twelve. Another solution to the low response rate could be to approach the riders differently. An alternative strategy would be to contact the platforms and with their help reach the riders. This has unsuccessfully been tried in the start of the process, but unfortunately was unsuccessful. However, for further research this strategy should be tried nonetheless.

A second limitation to the research is the assumption that the workers rationally choose the platform they want to work for. This *Homo Economicus* perspective on human behaviour is often used as basis for economic thinking and is one of the core elements of the argumentation from free market economics (DiMaggio & Goldberg, 2018). However, it is an assumption that is easily proven wrong. The choices and preferences of people are at least in part based on emotional response, which makes research based on the assumption that the choice of work arrangements being based on the weighing of work conditions fragile. A solution in further research could be to include a more in depth qualitive part in which on an inductive basis the factors of influence on people's choices for work arrangements are researched.

Lastly, reflecting on the measurement validity, there is an issue worth noting. In the final survey, in the alternatives presented to the respondents the control variables income level and delay of sick pay starting date were measured at the same time as the four main concepts in the discrete choice questions. If the survey would be used again, these concepts could have been measured at a less prominent place to leave more room for the respondent to think about their preferences on the core concepts.

5.6 Further research

When setting up and doing this research, ideas for further research have presented itself. Further research could focus on the differences between freelancers. For example, if fulltime freelancers have a different perspective on the gig economy's work arrangements compared to part-time freelancers. Such differences could be measured for example by asking for which part of their income freelancers are dependent on gig work.

A second research direction that could yield insights in the gig economy could be researching the monetary value of the four main independent variables. This could be done using the data gathered in this research. Appendix 3 contains a model in which the expected salary of a respondent is considered. The variable is computed by multiplying the per delivery income levels with the deliveries per hour, together with the wage per hour information form the income level variable. The model is not used for the purpose of this research, as it is not necessary to answer the main research question. However, it does contain interesting information about the monetary value of the attribute levels (see appendix 3). Questions that could be answered with this information are for example: how much can a worker's wage be decreased when insurance is introduced? Or how much more money does a hired worker need to be paid for him/her to switch to independent contractor work?

Another research direction that could be interesting is taking the research to an international scale. This would entail analysing the differences between gig workers in different countries. This would mean that several changes to the research must be made. First, the researches could focus on a different industry, because the food delivery industry is not as big in each country as it is in the Netherlands. In Dutch media, the debate on the gig economy focusses on the food delivery industry, and especially Deliveroo. However, in other parts of the world, taxi drivers associated with Uber is considered the main example of gig economy. Furthermore, the food delivery industry being at the centre of the discussion also means they have already adapted to the public's wishes. Applying similar research to other industries, insights can be derived regarding the influence of the public and political debate on the development of a concept like gig economy.

Additionally, the researches should consider including Varieties-of-Capitalism literature (See Hall, 2001). One could compare freelancers in central market economies with liberal market economies. It is conceivable that there would be a large difference in preferences for work conditions in work arrangements, due to the freelancer's expectancy of the differing work arrangements. For example, in the Netherlands it is common that an employer organizes social security measures for the employee. A certain level of care of the employer is expected when workers enter a contractual obligation with the employer. In liberal market economies, in which these kinds of institutions are not common, the freelancer compares the work arrangement offered by the gig platform to a totally different institutional environment. It would be interesting to see how this influences preferences for work conditions.

6. Conclusion

The internet facilitates the possibility for platforms to mediate between firms and workers. The new labour market dynamics that originate from this are referred to as the gig economy. In the gig economy, workers considered freelancers under traditional labour laws, work as independent contractors and are hired for one-time service jobs, often competing with traditional hired workers, who are on the payroll of the firm. The classification of independent contractor for the freelancer leads to changes in the work arrangements, which in the media are often depicted as exploitation of the workers. However, gig work is a trade-off, meaning there are positives that could potentially outweigh out the negatives. In this thesis this trade-off is analysed. Four concepts were used: sick pay, accident insurance, payment model and flexibility. Leading to the formulation of the question: 'How do preferences for flexibility, payment models, sick pay and accident insurance coverage differ between freelancers and hired workers?'

From the discrete choice experiment, conducted among workers in the Dutch food delivery industry, we can conclude on the following differences regarding the preferences of freelance gig workers and those of the hired gig workers. Regarding to working schedule, it was found that freelancers prefer working without schedules, in contrast to hired gig workers, who prefer scheduled work. Regarding payment models, both hired and freelancers prefer payment per hour rather than per delivery, although freelancers have a less negative attitude towards payment per delivery. For sick pay and accident insurance, no significant difference has been found between freelancers and hired workers. Both have the same degree of preference for longer sick pay periods and accident insurance coverage.

Ultimately, this research shows that freelancers have a lower demand for job and income securities like scheduled work and payment model compared to hired workers, but do not differ in preference on social securities like sick pay and accident insurance preferences.

Put in a broader perspective, it can be concluded that changes are required in the way platforms approach social securities. This change in approach could be reached by a bottom up consensus between platform and unified workers or top-down by government regulation on a basic social security safety net for independent contractors.

The gig economy platforms have found an innovative way to increase scalability of the workforce and a convenient way for workers to earn some money in their spare time. However, this comes with negatively perceived side effects like a decrease in social security in the work arrangements offered to the freelancers. Only the future can tell if the gig economy will be just a failed attempt at worker exploitation or a revolution in work allocation.

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References

Abraham, K. G., Haltiwanger, J. C., Sandusky, K., & Spletzer, J. R. (2017, March). Measuring the gig economy: current knowledge and open issues. In *IZA Labor Statistics Workshop "Changing Structure of Work*.

Ad.nl (2017, Sep 13). *Maaltijdbezorgers Deliveroo willen helemaal geen zzp'er zijn.* Accessed February 15, 2018. Available at https://www.ad.nl/economie/enlsquo-maaltijdbezorgers-deliveroo-willen-helemaal-geen-zzp-er-zijnenrsquo~ac9bc8a9/

Aguirre, F., Janibekova, G., Shamilov, T., Otmani, I., & Ellis, R. S. (2018). Extending social protections to workers in the sharing economy1. *Policy*, (1).

Aloisi, A. (2015). Commoditized workers: Case study research on labor law issues arising from a set of on-demand/gig economy platforms. *Comp. Lab. L. & Pol'y J.*, *37*, 653.

Bryman, A. (2015). *Social research methods*. Oxford university press.

Burtch, G., Carnahan, S., & Greenwood, B. N. (2018). Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science*.

Cahuc, P., Carcillo, S., & Zylberberg, A. (2014). *Labor economics*. MIT press.

Ciarniene, R., & Vienazindiene, M. (2018). Flexible Work Arrangements from Generation and Gender Perspectives: Evidence from Lithuania. *Engineering Economics*, *29*(1), 84-92.

De Stefano, V. (2015). The Rise of the Just-in-Time Workforce: On-Demand Work, Crowdwork, and Labor Protection in the Gig-Economy. *Comp. Lab. L. & Pol'y J.*, *37*, 471.

Deliveroo (n.d.) *Freelance FAQ.* Accessed February 15, 2018. Available at http://nl.roocommunity.com/2018/01/29/nederlands/

DiMaggio, P., & Goldberg, A. (2018). Searching for Homo Economicus: Variation in Americans' Construals of and Attitudes toward Markets. *European Journal of Sociology/Archives Européennes de Sociologie*, 1-39.

Etzioni, A. (2018). Benefits for Gig Workers. *Challenge*, 1-14.

Finkj, M. and W. Nagl (2018), Austria: How social protection rules affect self-employed and independent contractors, in *The Future of Social Protection: What Works for Non-standard Workers?*, OECD Publishing, Paris, https://doi.org/10.1787/9789264306943-6-en.

FNV. (n.d.). Min-max contract. Retrieved November 22, 2018, from https://www.fnv.nl/themas/contract/arbeidsovereenkomst/min-maxcontract/

Friedman, G. (2014). Workers without employers: shadow corporations and the rise of the gig economy. *Review of Keynesian Economics*, *2*(2), 171-188.

George, V. (2018). *Social security and society*. Routledge.

Green, D. D., Walker C., Alabulththim A., Smith D. & Phillips M. (2018). Fueling the Gig Economy: A Case Study Evaluation of Upwork. com. *Management and Economics Research Journal*, *4*(2018), 3399.

Graham, M., Hjorth, I., & Lehdonvirta, V. (2017). Digital labour and development: impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transfer: European Review of Labour and Research*, *23*(2), 135-162.

Gross, S. A., Musgrave, G., & Janciute, L. (2018). Well-Being and Mental Health in the Gig Economy.

Hall, P. A. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage*. D. W. Soskice (Ed.). Oxford: Oxford University Press.

Harris, S. D., & Krueger, A. B. (2015). *A Proposal for Modernizing Labor Laws for Twenty-First-Century Work: The" Independent Worker"*. Hamilton Project, Brookings.

Hoffman, S. D., & Duncan, G. J. (1988). Multinomial and conditional logit discrete-choice models in demography. *Demography*, *25*(3), 415-427.

Huws, U., Spencer, N. H., & Joyce, S. (2016). Crowd work in Europe: Preliminary results from a survey in the UK, Sweden, Germany, Austria and the Netherlands. *FEPS Studies, Foundation for European Progressive Studies, Brussels, December*.

Kuhn, K. M. (2016). The Rise of the "Gig Economy" and Implications for Understanding Work and Workers. *Industrial and Organizational Psychology*, *9*(1), 157-162.

Lehdonvirta, V. (2018). Flexibility in the gig economy: managing time on three online piecework platforms. *New Technology, Work and Employment*, *33*(1), 13-29.

Lobel, O. (2017). The Gig Economy & The Future of Employment and Labor Law. *USFL Rev.*, *51*, 51.

Malos, S., Lester, G. V., & Virick, M. (2018). Uber Drivers and Employment Status in the Gig Economy: Should Corporate Social Responsibility Tip the Scales?. *Employee Responsibilities and Rights Journal*, 1-13.

Marquis, E. B., Kim, S., Alahmad, R., Pierce, C. S., & Robert Jr, L. P. (2018). Impacts of Perceived Behavior Control and Emotional Labor on Gig Workers. In *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing* (pp. 241-244). ACM.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

Monazzam, M. R., & Soltanzadeh, A. (2009). The relationship between the worker's safety attitude and the registered accidents. *Journal of research in health sciences*, *9*(1), 17-20.

Muffels, R., & Luijkx, R. (2008). Labour market mobility and employment security of male employees in Europe: trade-off or flexicurity? *Work, employment and Society*, *22*(2), 221-242.

NOS.nl (2017, Aug 22). *Nieuwe Deliveroo bezorger kan alleen zzp'er zijn.* Accessed February 15, 2018. Available at https://nos.nl/artikel/2189252-nieuwe-deliveroo-bezorger-kan-alleen-zzp-er-zijn.html

NOS.nl (2018a, Jan 1) *Deliveroo-bezorgers Haarlem staken op drukste dag van het jaar.* Accessed February 15, 2018. Available at https://nos.nl/artikel/2210115-deliveroo-bezorgers-haarlem-staken-op-drukste-dag-van-het-jaar.html

NOS.nl (2018b, July 22). Maaltijdbezorgers hopen op meer rechten: 'zo kan het niet langer'. Retrieved November 21, 2018, from https://nos.nl/nieuwsuur/artikel/2242788-maaltijdbezorgers-hopen-op-meer-rechten-zo-kan-het-niet-langer.html

NOS.nl (2018c, July 23). Rechtbank: Deliveroo-bezorger is zzp'er en geen werknemer. Retrieved November 21, 2018, from https://nos.nl/artikel/2242846-rechtbank-deliveroo-bezorger-is-zzp-er-en-geen-werknemer.html

Nu.nl (2017, feb 14). *'Oneerlijke concurrentie' dwingt Foodora ook naar zzp-constructie te kijken.* Accessed February 15, 2018, available at https://www.nu.nl/economie/5133173/oneerlijke-concurrentie-dwingt-foodora-zzp-constructie-kijken.html

NU.nl. (2018a, June 06). Deliveroo in Spanje berispt om schijnzelfstandigheid bezorgers. Retrieved November 21, 2018, from https://www.nu.nl/carriere/5300690/deliveroo-in-spanje-berispt-schijnzelfstandigheid-bezorgers.html

NU.nl. (2018b, June 20). FNV: 'Minderjarigen bezorgen maaltijden voor Deliveroo'. Retrieved November 21, 2018, from https://www.nu.nl/carriere/5322287/fnv-minderjarigen-bezorgen-maaltijden-deliveroo.html

Osnowitz, D. (2010). *Freelancing expertise: contract professionals in the new economy*. Retrieved from https://ebookcentral.proquest.com

Posthumus, M. A. C., & Wilthagen, A. C. J. M. (2010). Zzp-ers en de transitionele arbeidsmarkt. *A. van Halem (red.), De opkomst van de zzp-er, Alphen aan den Rijn: Kluwer*, 27-35.

Ryan, M., Gerard, K., & Amaya-Amaya, M. (2008). Discrete choice experiments in a nutshell. In *Using discrete choice experiments to value health and health care* (pp. 13-46). Springer, Dordrecht.

Said, C. (2015, feb 17) *Growing voices say gig workers need protections, benefits.* Accessed February 15, 2018. Available at http://www.sfgate.com/business/article/Growing-voices-saygig-workers-need-protections-6079992.php

Schröder, H., & Ganzeboom, H. B. (2012). De waarde van diploma's in Nederland: de ESS-NL kwantificaties getoetst.

Shevchuk, A., Strebkov, D., & Davis, S. N. (2018). Work value orientations and worker well-being in the new economy: Implications of the job demands-resources model among internet freelancers. *International Journal of Sociology and Social Policy*, *38*(9/10), 736-753.

Singer, N. (2016). *In the Sharing Economy, Workers Find Both Freedom and Uncertainty.* Accessed February 15, 2018. Available at: http://www.nytimes.com/2014/08/17/technology/in-the-sharing-economy-workersfind-both-freedom-and-uncertainty.html?_r=0

Snider, L. (2018). Enabling Exploitation: Law in the Gig Economy. *Critical Criminology*, 1-15.

Sundararajan, A. (2016). *The sharing economy: The end of employment and the rise of crowd-based capitalism*. Mit Press.

UWV. (2014, August 15). Ik ben ziek en heb een werkgever. Retrieved November 12, 2018, from https://www.uwv.nl/particulieren/ziek/ziek-met-werkgever/inkomen-tijdens-ziekte/index.aspx

Van Boven, J. (2017, July 5) *Welke maaltijdbezorger past het best bij jou?* Accessed February 15, 2018. Available at https://www.metronieuws.nl/nieuws/binnenland/2017/07/welke-maaltijdbezorger-past-het-best-bij-jou

Van der Torre, W., Dirven, H. J., & van de Ven, H. (2018) Zzp'ers en werknemers: ongelijkheid in kwaliteit van werk. *Tijdschrift voor Arbeidsvraagstukken 2018 (34) 2,* 138-155

Witteman, J. (2017a, Nov 17) *Verplicht door als zzp'er? Deze 19-jarige fietskoerier sleept Deliveroo voor de rechter.* Accessed February 15, 2018. Available at https://www.volkskrant.nl/economie/verplicht-door-als-zzp-er-deze-19-jarige-fietskoerier-sleept-deliveroo-voor-de-rechter~a4539396/

Witteman, J. (2017b, Dec 1). *Hier bestelt maatschappelijk bewuste hongerlap het best zijn burgers en burrito's.* Accessed February 15, 2018. Available at https://www.volkskrant.nl/economie/hier-bestelt-maatschappelijk-bewuste-hongerlap-het-best-zijn-burgers-en-burrito-s~a4542529/

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2018). Good gig, bad gig: autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 0950017018785616.

Zwick, A. (2018). Welcome to the Gig Economy: neoliberal industrial relations and the case of Uber. *GeoJournal*, *83*(4), 679-691.

Appendices

Appendix 1: Example of survey

Dear respondent,

This questionnaire is about the trade-off made by food deliverers when choosing a firm to work for.

Firstly, we will ask you some introductionairy questions about who you are and how you work.

The second part of the questionnaire consists of twelve question related to your preference for certain working conditions. Two options will be presented to you, and you will be asked to choose the one most appealing to you. Secondly, you are asked to indicate if the option is realistic. The options differ on four points:

1. **Accident insurance**. Two options exist:
a. *Insured.* This means that all costs of an accident, like damages to cars or your bike, are paid by the insurance firm.
b. *Not insured.* This means that all costs of an accident are paid by you personally.

2. **Continuation of salary payment during illness**. Three options exist:
a. *No payment,* which means that when you can not work, no salary is paid.
b. *Direct payment,* which means you receive salary from the moment you get ill.
c. *Payment after two days,* which means you are not paid for the first two days of illness, but after that you will receive salary.

Additionally, the timespan of the sickness relief payments is varied between one week and two months.

3. **Division of work**. Two options exist:
a. *Through schedules*. When you work is determined by a schedule. You do have influece on which times you are available. When scheduled to work, you have to work even if there are no deliveries to be made.
b. *Without schedules*. You decide when to work, there is no planning. there is no guarantee that there are deliveries to be made.

4. **Wage**. Two options exist:
a. *Per hour*, you are paid per hour, regardless of having made many deliveries or none.
b. *Per delivery*, you are paid per delivery. The amount of time a delivery takes varies.

Additionally, the wage level is varied between €3 per delivery and €14 per hour.

The answers you provide are stored anonymous and are not traceble to you personally. If you have a question or other comment, send me an email at J.J.deSwart@UU.nl.

Thank you in advance for filling in the survey!
Kind regards,
Jelle de Swart

What is your age?

[ ] years

What is your gender?

- ◯ Man
- ◯ Woman
- ◯ Other [ ]

What is your highest fullfilled education?

- ◯ Elementary school
- ◯ High school
- ◯ Practical education (MBO)
- ◯ Applied University (HBO)
- ◯ University Bachelor
- ◯ University Master
- ◯ Other [ ]

0% 100%

In which city do you work?

Which means of transportation do you use to work?

Multiple options can be chosen

- [ ] Bike
- [ ] Electric bike
- [ ] Moped
- [ ] Other

How many deliveries do you make per hour on average?

0% 100%

How many hours did you work for these firms last month?

	Hours
UberEats	
Deliveroo	
Foodora	
Thuisbezorgd.nl	

0% 100%

This question is randomized for each respondent, and will be asked twelve times. Each time, the attribute levels are randomized.

Which option has your preference?
Click here for explanation

(1 of 12)

Accident insurance	Not insured	Insured
Payment when ill	No payment when ill	No payment
Division of work	Via schedule	Without schedule
Salaris	€3 Per delivery	€10 Per hour
	Select	Select

In reality, would you choose this option?

Yes No

0% 100%

This is the end of the questionnaire. Thank you for your contribution!

Powered by Sawtooth Software

0% 100%

Appendix 2: R-script

```
library(readr)
#install.packages('splitstackshape')
library(splitstackshape)
library(survival)
#install.packages('xlsx')
require(lattice)
library('xlsx')
#install.packages("car")
library(car)
library(rms)

design_mat <- read_csv("~/Master
Thesis/Results4real/SurveyR4R/Design/CBCExport/CBC1_design.cs
v")
design_mat = as.data.frame(design_mat)
response_mat <- read_csv("~/Master
Thesis/Results4real/SurveyR4R/Design/CBCExport/CBC1_response
s.csv")
response_mat = as.data.frame(response_mat)
dat_gig <- read.csv("~/Master
Thesis/Results4real/SurveyR4R/gig/RawExport/RawExport.csv")
dat_gig <- as.data.frame(dat_gig)
convar <- read.csv("~/Master
Thesis/Results4real/controlvariables.csv")
convar$resID <- convar$ï..sys_RespNum
## page time
convar$pagetime <- convar$sys_pagetime_2 +
convar$sys_pagetime_3 +
convar$sys_pagetime_4+convar$sys_pagetime_5+convar$sys_pag
etime_6+
convar$sys_pagetime_7+convar$sys_pagetime_8+convar$sys_pag
etime_9+convar$sys_pagetime_10+convar$sys_pagetime_11+con
var$sys_pagetime_12+
 convar$sys_pagetime_13+convar$sys_pagetime_14
for(i in 1:nrow(convar)){
 if(convar$pagetime[i] > 1200){
  convar$pagetime[i] <- NA
 }
}
convar <- convar[c("resID","Leeftijd", "Opleiding",
"Vervoersmiddel_1", "Vervoersmiddel_2","Vervoersmiddel_3",
"Geslacht", "UurGewerkt_r1_c1",
"UurGewerkt_r2_c1","UurGewerkt_r3_c1","UurGewerkt_r4_c1","
Bezorgd", "pagetime")]
convar = expandRows(dataset = convar, count = 24, count.is.col =
F)
response = rep(response_mat[,1], times=1, each=24)
task = rep(1:12, times = 102, each = 2)
result = data.frame(response, task)
# for every respondent, do:
res_mat = data.frame(row.names = c())
for(j in 1:102){
 respondent = rep(response_mat[j,1], 24)
 version = response_mat[j,2]
 submat = subset(design_mat, design_mat$Version==version)
 A_mat = submat[,4:8]
  #choice
 choice_temp = c()
 for(i in 1:12){
  choice_temp[i] = response_mat[j,(2*i+1)]
 }
 choice = c()
 for(i in 1:12){
  if(choice_temp[i]==1){
   choice[(2*i-1)] = 1
   choice[(2*i)] = 0
  }
  else{
   choice[(2*i-1)] = 0
   choice[(2*i)] = 1
  }
 }
 choice
  #none 0=niet gekozen in het echt 1=gekozen
 none = c()
 for(i in 1:12){
  none_temp = response_mat[j,(2*i+2)]
  if(none_temp == 1){
   none[(2*i-1)] = 1
   none[(2*i)] = 1
  }
  else{
```

```
    none[(2*i-1)] = 0
    none[(2*i)] = 0
   }
  }
  res = cbind(respondent, A_mat, choice, none)
  res_mat = rbind(res_mat, res)
}
res_mat$choiceid = rep(1:12, times = 102, each = 2)
res_mat$choice = res_mat$choice==1
res_mat$alt = rep(c('A', 'B'), 1224)
## Payment when ill
for(i in 1:length(res_mat[,1])){
  if(res_mat$`Payment when ill`[i]== 1){
    res_mat$delay[i]<- NA
    res_mat$duration[i]<- 0
  }
  if(res_mat$`Payment when ill`[i]== 2){
    res_mat$delay[i]<- 2
    res_mat$duration[i]<- 7
  }
  if(res_mat$`Payment when ill`[i]== 3){
    res_mat$delay[i]<- 2
    res_mat$duration[i]<- 30
  }
  if(res_mat$`Payment when ill`[i]== 4){
    res_mat$delay[i]<- 2
    res_mat$duration[i]<- 60
  }
  if(res_mat$`Payment when ill`[i]== 5){
    res_mat$delay[i]<- 0
    res_mat$duration[i]<- 7
  }
  if(res_mat$`Payment when ill`[i]== 6){
    res_mat$delay[i]<- 0
    res_mat$duration[i]<- 30
  }
  if(res_mat$`Payment when ill`[i]== 7){
    res_mat$delay[i]<- 0
    res_mat$duration[i]<- 60
  }
  if(res_mat$`Payment when ill`[i]== 8){
    res_mat$delay[i]<- NA
    res_mat$duration[i]<- 0
  }
}
## wage variable
res_mat$wagecat <- res_mat$Wage
for(i in 1:length(res_mat[,1])){
  if(res_mat$`Wage`[i]== 5){
    res_mat$wagecat[i]<- 1
  }
  if(res_mat$`Wage`[i]== 6){
    res_mat$wagecat[i]<- 2
  }
  if(res_mat$`Wage`[i]== 7){
    res_mat$wagecat[i]<- 3
  }
  if(res_mat$`Wage`[i]== 8){
    res_mat$wagecat[i]<- 4
  }
}
#Accident Insurance 1= insured, 0=not insured
res_mat$AI = res_mat$`Accident insurance`*-1+2
#Division of Work 1=via schedule, 0=without schedule
res_mat$DOW = res_mat$`Division of work`*-1+2
#gig
res_mat$gig = rep(dat_gig$Giggers, times = 1, each = 24)
#Salaris vorm 1= per delivery, 0= per hour
res_mat$SV = res_mat$`Salaris vorm`*-1+2
#Interaction
res_mat$int.AI <- res_mat$gig*res_mat$AI
res_mat$int.DOW <- res_mat$gig*res_mat$DOW
res_mat$int.SV <- res_mat$gig*res_mat$SV
#res_mat$int.dur < res_mat$gig*res_mat$duration
col_name = colnames(res_mat)
col_name[1] = 'id'
colnames(res_mat) = col_name
#per monetary value calculation
for(i in 1:nrow(res_mat)){
  if(res_mat$SV[i] == 1){ #per delivery
    res_mat$money[i]<- (res_mat$Wage[i]+2)*convar$Bezorgd[i]
  }
  if(res_mat$SV[i] == 0){ #per hour
    res_mat$money[i]<- res_mat$Wage[i]*2-2
  }
}
#for strata
res_mat$stratum <-rep(1:(0.5*nrow(res_mat)), each = 2)
res_mat$chid = rep(1:(length(res_mat[,1])/2), times = 1, each = 2)
res_mat <- res_mat[c("id", "choiceid","stratum", "choice", 'alt'
,"SV" , "DOW", "AI", "int.SV" ,  "int.DOW", "int.AI", "delay",
"duration", "wagecat", "none", "gig", "chid", "Salaris
vorm","Accident insurance", "Payment when ill", "Division of
work", "Wage", "none", "money")]
res_mat$BG <- res_mat$id
for(i in 1:nrow(res_mat)){
  if(res_mat$BG[i]<= 106){ res_mat$BG[i] <- 0}
  if(res_mat$BG[i]> 106){ res_mat$BG[i] <- 1}
}
temp_mat = res_mat
#control variables
#Vervoersmiddel 1=bike
convar$Vervoersmiddel_2<- convar$Vervoersmiddel_2*2 #Electric
bike
convar$Vervoersmiddel_3<- convar$Vervoersmiddel_3*3 #Moped
convar$Vervoersmiddel <-
convar$Vervoersmiddel_1+convar$Vervoersmiddel_2+convar$Ver
voersmiddel_3
for(i in 1:nrow(convar)){
  if(convar$Vervoersmiddel[i] == 4 || 0){
    convar$Vervoersmiddel[i] <- NA
  }
}
#geslacht 0=female 1=male
convar$gender = convar$`Geslacht`*-1+2
#Uur gewerkt
convar$UG <- convar$UurGewerkt_r1_c1 +
convar$UurGewerkt_r2_c1 + convar$UurGewerkt_r3_c1 +
convar$UurGewerkt_r4_c1
#education
edu2 <- subset(convar, convar$resID > 106)
edu <- subset(convar, convar$resID <= 106)
for(i in 1:nrow(edu)){
  if (edu$Opleiding[i] == 3){edu$Opleiding[i] <- 2}}
for(i in 1:nrow(edu)){
  if (edu$Opleiding[i] == 4){edu$Opleiding[i] <- 2}}
for(i in 1:nrow(edu)){
  if (edu$Opleiding[i] == 5){edu$Opleiding[i] <- 3}}
for(i in 1:nrow(edu)){
  if (edu$Opleiding[i] == 6){edu$Opleiding[i] <- 4}}
for(i in 1:nrow(edu)){
  if (edu$Opleiding[i] == 7){edu$Opleiding[i] <- 5}}
```

```
for(i in 1:nrow(edu)){
 if (edu$Opleiding[i] == 8){edu$Opleiding[i] <- 6}}
for(i in 1:nrow(edu)){
 if (edu$Opleiding[i] == 9){edu$Opleiding[i] <- 7}}
convar <- rbind(edu, edu2)
for(i in 1:nrow(convar)){
 if(convar$Opleiding[i] == 1){ convar$Opleiding[i]<- 0.258}
 if(convar$Opleiding[i] == 2){ convar$Opleiding[i]<- 0.541}
 if(convar$Opleiding[i] == 3){ convar$Opleiding[i]<- 0.530}
 if(convar$Opleiding[i] == 4){ convar$Opleiding[i]<- 0.612}
 if(convar$Opleiding[i] == 5){ convar$Opleiding[i]<- 0.841}
 if(convar$Opleiding[i] == 6){ convar$Opleiding[i]<- 0.878}
 if(convar$Opleiding[i] == 7){ convar$Opleiding[i]<- NA}
}
#Control Variables aan res_mat
CV <- convar[c("resID","Leeftijd", "Opleiding", "Vervoersmiddel",
"gender", "UG","Bezorgd", "pagetime")]
totdat <- cbind( res_mat, CV)
#none eruit
totdat <- subset(totdat, totdat$none==1)
# centring
totdat$Leeftijdold <- totdat$Leeftijd
totdat$Leeftijd <- scale(totdat$Leeftijd, cente = TRUE, scale =
FALSE)
totdat$UGold <- totdat$UG
totdat$UG <- scale(totdat$UG, center = TRUE, scale = FALSE)
totdat$Bezorgdold <- totdat$Bezorgd
totdat$Bezorgd <- scale(totdat$Bezorgd, center = TRUE, scale =
FALSE)
totdat$pagetimeold <- totdat$pagetime
totdat$pagetime <- scale(totdat$pagetime, center = TRUE, scale =
FALSE)
totdat$Opleidingold <- totdat$Opleiding
totdat$Opleiding <- scale(totdat$Opleiding, center= TRUE, scale =
FALSE)
#control vavriable interaction
#age
totdat$agedur <- totdat$Leeftijd*totdat$duration
totdat$agedel <- totdat$Leeftijd*totdat$delay
totdat$ageai  <- totdat$Leeftijd*totdat$AI
totdat$agedow <- totdat$Leeftijd*totdat$DOW
totdat$agesv  <- totdat$Leeftijd*totdat$SV
totdat$agewl  <- totdat$Leeftijd*totdat$wagecat
totdat$agemon <- totdat$Leeftijd*totdat$money
#Opleiding
totdat$edudur <- totdat$Opleiding*totdat$duration
totdat$edudel <- totdat$Opleiding*totdat$delay
totdat$eduai  <- totdat$Opleiding*totdat$AI
totdat$edudow <- totdat$Opleiding*totdat$DOW
totdat$eduwl  <- totdat$Opleiding*totdat$wagecat
totdat$edumon <- totdat$Opleiding*totdat$money
#vervoers
totdat$verdur <- totdat$Vervoersmiddel*totdat$duration
totdat$verdel <- totdat$Vervoersmiddel*totdat$delay
totdat$verai  <- totdat$Vervoersmiddel*totdat$AI
totdat$verdow <- totdat$Vervoersmiddel*totdat$DOW
totdat$versv  <- totdat$Vervoersmiddel*totdat$SV
totdat$verwl  <- totdat$Vervoersmiddel*totdat$wagecat
totdat$vermon <- totdat$Vervoersmiddel*totdat$money
#Gender
totdat$gendur <- totdat$gender*totdat$duration
totdat$gendel <- totdat$gender*totdat$delay
totdat$genai  <- totdat$gender*totdat$AI
totdat$gendow <- totdat$gender*totdat$DOW
totdat$gensv  <- totdat$gender*totdat$SV
totdat$genwl  <- totdat$gender*totdat$wagecat
totdat$genmon <- totdat$gender*totdat$money
#UG
totdat$ugxdur <- totdat$UG*totdat$duration
totdat$ugxdel <- totdat$UG*totdat$delay
totdat$ugxai  <- totdat$UG*totdat$AI
totdat$ugxdow <- totdat$UG*totdat$DOW
totdat$ugxsv  <- totdat$UG*totdat$SV
totdat$ugxwl  <- totdat$UG*totdat$wagecat
totdat$ugxmon <- totdat$UG*totdat$money
#Bezorgd
totdat$bezdur <- totdat$Bezorgd*totdat$duration
totdat$bezdel <- totdat$Bezorgd*totdat$delay
totdat$bezai  <- totdat$Bezorgd*totdat$AI
totdat$bezdow <- totdat$Bezorgd*totdat$DOW
totdat$bezsv  <- totdat$Bezorgd*totdat$SV
totdat$bezwl  <- totdat$Bezorgd*totdat$wagecat
totdat$bezmon <- totdat$Bezorgd*totdat$money
#wagecat
totdat$wcdur <- totdat$wagecat*totdat$duration
totdat$wcai  <- totdat$wagecat*totdat$AI
totdat$wcdow <- totdat$wagecat*totdat$DOW
totdat$wcsv  <- totdat$wagecat*totdat$SV
#delay
totdat$deldur <- totdat$delay*totdat$duration
#time
totdat$timedur <- totdat$pagetime*totdat$duration
totdat$timeai <- totdat$pagetime*totdat$AI
totdat$timedow <- totdat$pagetime*totdat$DOW
totdat$timesv <- totdat$pagetime*totdat$SV
totdat$timemon <- totdat$pagetime*totdat$money
##Background
totdat$bgxdur <- totdat$BG*totdat$duration
totdat$bgxai  <- totdat$BG*totdat$AI
totdat$bgxdow <- totdat$BG*totdat$DOW
totdat$bgxsv  <- totdat$BG*totdat$SV
totdat$bgxmon <- totdat$BG*totdat$money
totdat$int.dur <- totdat$gig*totdat$duration
totdat$gigdur <- totdat$gig*totdat$duration
totdat$gigAI <- totdat$gig*totdat$AI
totdat$gigDOW <- totdat$gig * totdat$DOW
totdat$gigSV <- totdat$gig*totdat$SV
totdat$gigmon <- totdat$gig*totdat$money
fit1 = clogit(choice ~ duration + AI + DOW + SV + strata(stratum),
data = totdat, method = "efron")
fit2 = clogit(choice ~ duration + AI + DOW + SV + gigdur + gigAI +
gigDOW  + gigSV + strata(stratum), data = totdat, method =
"efron")
fit3 = clogit(choice ~ duration + AI + DOW + SV + gigdur+ gigAI+
gigDOW  + gigSV  + agedur  + ageai +
        agedow + agesv +  timedur + timedow + timeai + timesv +
ugxdur + ugxai + ugxsv +
        eduai + edudow + wagecat + delay + bgxdur + bgxsv +
bgxdow + bgxai +
        + bezdur + bezsv +  strata(stratum), data = totdat, method
= "efron")
u <- 0
vif1 <- car::vif(fit1)
vif2 <- car::vif(fit2)
vif3 <- car::vif(fit3)
Output1 <- function(t,w){
 u <<- u+1
  w <- as.matrix(w)
  VIFF <- w[,1]
  VIFF <- VIFF[1:(length(VIFF)-1)]
```

```
 Names <- row.names(t)
  Coefficient <- t[,1]
  Pvalue <- t[,5]
  SE <- t[,3]
 Sig <- c("")
  Coefficient <- format(round(Coefficient, 3), nsmall = 3, justify =
"right")
 Pvalue <- format(round(Pvalue, 3), nsmall = 3, justify = "right")
 SE <- format(round(SE, 3), nsmall = 3, justify = "right")
 VIFF <- format(round(VIFF, 3), nsmall = 3, justify = "right")
  e <- cbind(Names, Coefficient,Pvalue, Sig, SE, VIFF)
 for (i in 1:length(Pvalue)){
  if(Pvalue[i] <= 0.05){e[i,4]<- "<0.05"}
  if(Pvalue[i] <= 0.01){e[i,4]<- "<0.01"}
  if(Pvalue[i] <= 0.001){e[i,4]<- "<0.001"}
 }
 row.names(e) <- e[,1]
 e <- e[,2:ncol(e)]
 if(u == 1){
  write.xlsx(e, "resultsmodelA.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 2){
  write.xlsx(e, "resultsmodelB.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 3){
  write.xlsx(e, "resultsmodelC.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 4){
  write.xlsx(e, "resultsmodelMonA.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 5){
  write.xlsx(e, "resultsmodelMonB.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 6){
  write.xlsx(e, "resultsmodelMonC.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
}
Output1(summary(fit1)[["coefficients"]], vif1)
Output1(summary(fit2)[["coefficients"]], vif2)
Output1(summary(fit3)[["coefficients"]], vif3)
print(summary(fit1)[["rsq"]])
print(summary(fit2)[["rsq"]])
print(summary(fit3)[["rsq"]])
u <- 0
Output2 <- function(t){
 u <<- u+1
 #w <- as.matrix(w)
 #VIFF <- w[,1]
 #VIFF <- VIFF[1:(length(VIFF)-1)]
 Names <- row.names(t)
 Coefficient <- t[,1]
 Pvalue <- t[,5]
 SE <- t[,3]
 Sig <- c("")
  Coefficient <- format(round(Coefficient, 3), nsmall = 3, justify =
"right")
 Pvalue <- format(round(Pvalue, 3), nsmall = 3, justify = "right")
 SE <- format(round(SE, 3), nsmall = 3, justify = "right")
 #VIFF <- format(round(VIFF, 3), nsmall = 3, justify = "right")
  e <- cbind(Names, Coefficient,Pvalue, Sig, SE)
 for (i in 1:length(Pvalue)){
  if(Pvalue[i] <= 0.05){e[i,4]<- "<0.05"}
  if(Pvalue[i] <= 0.01){e[i,4]<- "<0.01"}
  if(Pvalue[i] <= 0.001){e[i,4]<- "<0.001"}
 }
  row.names(e) <- e[,1]
 e <- e[,2:ncol(e)]
  if(u == 1){
  write.xlsx(e, "resultsmodelAMONEY.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 2){
  write.xlsx(e, "resultsmodelBMONEY.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 if(u == 3){
  write.xlsx(e, "resultsmodelCMONEY.xlsx", sheetName="Sheet1",
           col.names=TRUE, row.names=TRUE, append=FALSE,
showNA=TRUE, password=NULL)}
 }
fit4 = clogit(choice ~ duration + AI + DOW + money +
strata(stratum), data = totdat, method = "efron")
fit5 = clogit(choice ~ gig*duration + AI*gig + DOW*gig +
money*gig + strata(stratum), data = totdat, method = "efron")
fit6 = clogit(choice ~ duration + AI + DOW + money + gigdur+
gigAI+ gigDOW  + gigmon  + agedur  + ageai +
            agedow + agemon +  timedur + timedow + timeai +
timemon + ugxdur + ugxai + ugxmon +
            eduai + edudow + delay + bgxdur + bgxmon + bgxdow +
bgxai + strata(stratum), data = totdat, method = "efron")
u <- 0
Output2(summary(fit4)[["coefficients"]])
Output2(summary(fit5)[["coefficients"]])
Output2(summary(fit6)[["coefficients"]])
print(summary(fit4)[["rsq"]])
print(summary(fit5)[["rsq"]])
print(summary(fit6)[["rsq"]])
u <- 0
```

Appendix 3: Model with expected salary

In the survey, in all the options presented to the respondent the salary was further specified to a range between €3 and €6 per delivery, or €8 to €14 per hour. Using the control variable which provides data on the amount of rides a respondent expects to make in an hour, an expected salary variable could be computed. This model is like model B, except the payment model variable is replaced by the expected salary variable. Using this model, the relative monetary value of the variables in the model is calculated.

The descriptive statistics on the expected salary variable are presented in table A1. The results of this analysis are presented in table A2.

Table A1: Descriptive statistics of expected salary variable

Min	1st quadrant	Median	Mean	3rd quadrant	Max	NA
6	10	12	12.71	14	60	0

Table A2: Results expected salary model

Explanatory Variables	Model A	Model B	Model C
Sick pay	0.007*** (0.002)	0.006* (0.003)	0.002 (0.004)
Accident insurance	0.519*** (0.079)	0.512*** (0.097)	0.728*** (0.169)
Flexibility	0.074 (0.081)	0.339*** (0.100)	0.532*** (0.166)
Expected salary	-0.007 (0.008)	-0.032** (0.011)	-0.038 (0.023)
Work model x Sick pay		0.003 (0.005)	0.004 (0.555)
Work model x Accident insurance		0.028 (0.175)	-0.254 (0.346)
Work model x Flexibility		-0.830*** (0.179)	-0.855*** (0.001)
Work model x Expected salary		0.077*** (0.021)	0.055 (0.164)
Age x Sick pay			-0.000 (0.515)
Age x Accident Insurance			0.047 (0.141)
Age x Flexibility			0.020 (0.509)
Age x Expected salary			-0.002 (0.600)
Survey completion time x Sick pay			0.000 (0.448)
Survey completion time x Flexibility			-0.001 (0.218)
Survey completion time x Accident insurance			-0.001 (0.282)
Survey completion time x Expected salary			0.000** (0.010)
Hours worked x Sick pay			0.000

			(0.704)
Hours worked x Accident Insurance			0.002 (0.346)
Hours worked x Expected salary			0.001 (0.113)
Education x Accident Insurance			0.958 (0.347)
Education x Flexibility			1.026 (0.309)
Delay			-0.070 (0.296)
Nationality x Sick pay			-0.007 (0.352)
Nationality x Expected salary			0.041 (0.339)
Nationality x Flexibility			-0.495* (0.0.093)
Nationality x Accident Insurance			-0.872** (0.003)
N	936	936	936
Concordance	0.608	0.643	0.656
R-square	0.032	0.051	0.053
Likelihood ratio test	60.25	98.92	68.09
Df	4	8	26
Wald test	56.48	85.25	52.92

Interestingly, replacing the payment model, income level and deliveries per hour variable by expected salary does lead to a decrease of model performance of about 10-15 %. Additionally, the expected salary variable is not significant in model A and C. However, using these numbers the relative value of attributes is calculatable. This can be done for the coefficients of the variables of model C, by dividing the coefficient of the attribute over the coefficient of the expected salary variable (see formula A1). The results of this are shown in table A3. This can be interpreted that workers are willing to earn €0.05 less when they do get sick pay one day longer.

$$Value\ of\ attribute = \frac{Coefficient\ of\ attribute}{Coefficient\ of\ expected\ salary}\ (A1)$$

To calculate the difference between freelancers and hired workers, the coefficient of the interaction term should be subtracted from the direct effect. The remaining coefficient should be divided by the expected salary coefficient (see formula A2). The results can be interpreted as hired workers being prepared to earn

€0.05 per hour less than freelancers if they get one day more sick pay. Interestingly, freelancers want to earn €36.50 more than hired workers if they need to work scheduled.

$$Value\ of\ attribute = \frac{Coefficient\ of\ direct\ effect - \ Coefficient\ of\ interaction\ effect}{Coefficient\ of\ expected\ salary}\ (A2)$$

Table A3: results of calculations of monetary value of attributes

Variable	**Value**
Sick pay	€-0.05
Accident insurance	€-19.16
Flexibility	€-14.00
Work model x Sick pay	€0.05
Work model x Accident insurance	€-25.84
Work model x Flexibility	€-36.50