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A Subtle Invitation to Bargain: Online Vacancy Data-based Inquiry into the Wage Setting Policies of Latvian Employers

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/Ēriks Kasparenoks/ /Dana Supe/

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Abstract

Using a novel online job vacancy dataset, we examine the extent of wage negotiations in the Latvian labor market from the employer's perspective. We establish a connection between the type of wage advertised and a firm's willingness to engage in wage bargaining. We employ logit and tobit models and find that a company is more likely to negotiate an employee's wage when the job advertised needs higher qualification. Wage bargaining is also more prevalent, and firms are more open to wage negotiations in industries where employee productivity is heterogenous and workers are scarce. In addition, larger companies negotiate less with their employees. We also find that in Latvia, wages are negotiated more in Kurzeme, Zemgale, Vidzeme, and less in Latgale regions. Our findings are robust to alternative model specifications and modified assumptions. This research adds to wage negotiation research as well as aids firms and employees in understanding wage bargaining dynamics.

JEL code: J31, J33

1. Introduction

Labor economics has often looked at how potential employees meet their employers and how they arrive at the final employment decision. A key ingredient to any labor relationship is a wage that a firm pays, and a worker receives. Furthermore, there are two main mechanisms to arrive at this wage: employers can choose whether to offer a fixed wage or negotiate the actual salary with the potential employee.

Choosing to bargain or set a wage has implications for a firm's productivity and costs: by setting one wage, firms make the process simpler and cut down on recruitment and wage costs. On the other hand, when firms start wage bargaining, employees are likely to negotiate for a higher salary, thus, raising costs for the firm. But this, in turn, lets a firm hire more productive and motivated workers (Ellingsen & Rosén, 2003; Michelacci & Suarez, 2006). We apply these concepts in our work and research the firm's initial choice to offer one fixed wage or indicate that they are open to bargaining, employing an online vacancy dataset and conducting quantitative analysis.

Apart from firms, wage-setting mechanisms are important for workers: by understanding whether companies are open to bargaining, they can use this to their advantage and know when it is possible to extract higher wages. Wage policies, including wage negotiations, are also a widely researched topic among labor economists. One aspect of the firm's choice between offering a fixed wage or bargaining is that wage bargaining works as a redistribution mechanism, allowing more productive workers to also earn more. However, an increase in wage bargaining may also increase unemployment and add to wage inequality in the economy, which is relevant for policymakers to consider (Michelacci and Suarez, 2006). In short, being able to assess the extent of wage negotiations in a particular country allows for insights into firm priorities concerning productivity or costs, employee bargaining power, and the macroeconomy.

From the empirical perspective, Brenzel et al. (2014) look at whether firms post a fixed wage or bargain. We base our approach on their work, because, alongside personal characteristics, they add company-side determinants to explore the issue from the firm's perspective. Brenčič (2012) examines the same firm behavior on wage-setting using data from job advertisement sites. She justifies the use of job ads for such a research by claiming that, in reality, firms may decide whether to bargain or propose a set wage already before the interview process - in vacancy advertisements. This forms one of the pillars of our research:

firms who do not post a wage and expect bargaining in the interview process behave similarly to those firms who post flexible, negotiable wages in their job advertisements (Brenčič, 2012). Negotiable wage postings include advertising a wage range (e.g. EUR 730-1000), wage minimum (e.g. starting from EUR 730), or maximum (e.g. up to EUR 1000) as opposed to one exact wage (e.g. EUR 730), which indicates a non-negotiable salary. Of particular interest for us, Brenčič (2012) has also found that wider ranges in the job ads are an indicator that the wages will be negotiated because they are less descriptive of the actual future wage. Because of this, we can use web vacancy data to analyze the issue and interpret the wage range as openness to negotiation.

In Latvia, there is a legal obligation for firms to report the wage for a vacancy since 2018 (Labour Law 2018, s. 32). This implies that all occupation and industry job seekers in Latvia have information about their potential salary before interviews. The absence of such a rule has limited similar research in other markets. Both Hall & Krueger (2012) and Brenčič (2012) report that only a fraction of job seekers have information about their future wage, mostly union and government workers. In addition, this new law increased engagement in job ad portals: Zalāne (2019) reports that the unique visitor count of the cv.lv website increased by 25% after the law that introduced mandatory posting of wages. Thus, we believe that Latvia is quite a unique case and allows for new insights into the topic.

To our knowledge, research about wage negotiations or bargaining has not been carried out in Latvia. In addition, previous research has relied on survey data, which is known to be dependent on the respondent's recall of the situation, suffers from selection bias[1] and offers no information about firm's initial choices to offer negotiable or fixed wages (Hall & Krueger, 2012; Brenčič, 2012). In contrast, researchers point to the advantages of using online data in labor economics: a large number of observations, real-time nature and high posting frequency allow for more representativeness and sometimes even more explanatory power than labor market survey data (Carnevale et al., 2014; Deming & Kahn, 2018).

To fully utilize novel data availability introduced by the Latvian law, in the first part of our analysis, we plan to replicate the work of Brenzel et al. (2014). They explore the probability of a firm opting for wage negotiations or fixed wage-setting using various individual and firm characteristics by employing Germany's Job Vacancy Survey and using the logit model. We make slight modifications to their research and look at the prevalence of

[1] It is only known what happens to people who got the job.

wage negotiations in Latvia. Thus, our first research question is: **what are the determinants of the firm's choice to post a fixed wage or a wage range in a job ad in Latvia?** Subsequently, as online vacancy data offers information about numerical data on the offered wages[2] , we are also able to add to the existing body of research by using tobit analysis and explore: **what impacts the extent of a firm's openness to negotiation in Latvia[3]?**

Our dataset is constructed from online job adverts in Latvia posted on such websites as cv.lv, cvmarket.lv visidarbi.lv, teirdarbs.lv and the website of the State Employment Agency of Latvia. Online job postings have information about the company, wage, location, and job type. We extend our database by adding information about the company such as size, profitability, and industry classifications. The final dataset is comprised of 7395 private sector observations for job adverts that are posted online from November 2020 to January 2021. We claim that our dataset is representable of the whole Latvian labor market, since it constitutes 68.64% of the total average vacancy count in 2020 (Central Statistical Bureau of Latvia, 2020a).

The main findings of our research indicate that firms allow for more negotiations with highly skilled professionals and for workers in those industries where the productivity of employees is substantially different. We find that larger firms negotiate less and post more fixed wages, whereas profitability of the firm and part-time job indication are not important factors for determining wage bargaining in Latvia. Finally, negotiations are more prevalent in Kurzeme, Zemgale and Vidzeme regions when compared to Rīga, and less prevalent in Latgale.

The rest of the sections of the paper are organized in the following way. We start with the Literature Review where we explore theoretical grounds for this research, look at empirical findings, and form hypotheses based on the work of Brenzel et al. (2014). Next, we consider the strengths and weaknesses of our dataset in the Use of Online Vacancy Data section. Next, we explain our dataset and methodological approach. In the end, we present our regression results and robustness tests, combine theory with empirical findings as well as touch upon limitations of our work in the discussion.

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[2] In contrast to survey data where respondents answer "yes" if they bargained with their employer and "no" if they did not.

[3] Measured as the wage range.

2. Literature Review

In the Literature Review section, we start by looking at the theoretical justification of our research – relationship between an employee and employer, search-matching frictions, and the implications for firms between choosing to negotiate or to offer one fixed wage. Next, we look at empirical research carried out on the matter. Lastly, we introduce specific determinants of wage negotiations.

2.1. Wage Setting and Openness to Negotiations

A topic widely researched in the labor economics literature is the process of a job seeker finding his employer, otherwise known as the labor search-matching model. In this model, there are unemployed workers who are looking for jobs, and vacancies created by firms who are looking for workers. The relationship between a job seeker and a job giver arriving at an employment opportunity is modeled by the matching function - it displays jobs actually created by firms hiring suitable employees (Petrongolo & Pissarides, 2001). However, this matching process is lengthy, expensive, and complicated because of various costs of recruitment. In the labor research literature, these costs are called search-matching frictions. Frictions imply that employers might miss out on potentially advantageous and profitable employment opportunities and vice versa (Mortensen & Pissarides, 1999).

Search-matching frictions influence the labor market by causing fluctuations in unemployment levels and vacancy openings. Firms adjust their wage policies to attract needed candidates in a tight labor market and to reduce labor and recruitment costs when unemployment is high (Ellingsen and Rosén, 2003). However, companies need to not only decide on what wage will they offer for new hires but also what kind of wage will they initially advertise as this attracts a different kind of workers (Michelacci & Suarez, 2006). Usually, there are two approaches to this. The first one is referred to as fixed wage posting and involves the employee receiving a job and an exact, “take-it-or-leave-it” wage offer. The second is wage bargaining and refers to salary negotiations between the firm and the potential employee (Brenzel et al., 2014).

If a firm decides to offer a fixed wage in an advertisement, only workers who are satisfied with this wage will apply for the position. The costs (such as time and effort) of continuing the search for another job are higher than benefits from accepting this employment possibility. In this case, the company does not have to negotiate with employees, making the process of filling a vacancy shorter and cheaper and, thus, lowering the recruitment and wage costs. On the other hand, a sizeable portion of jobseekers who seek wages higher than the offered ones (more productive workers) will forgo possible employment with the company. This creates an adverse selection problem for the firm – even if it can decrease recruitment costs by offering one fixed wage, it is likely to get less productive employees (Ellingsen & Rosén, 2003; Michelacci & Suarez, 2006).

On the other hand, if a firm negotiates the wage with its employees, it is more flexible and can adjust the salary to hire workers who are seeking higher wages. The downside here is that job seekers can extract higher wages at a company's expense. However, they are also likely to be much more productive than those who accepted fixed wages. This is so because more productive employees have higher bargaining power, get higher utility from higher wages, and are simply more attracted to a vacancy where they will be able to negotiate their wage (Ellingsen & Rosén, 2003; Michelacci & Suarez, 2006). As a result, even though these firms incur higher costs, the workers they hire also produce more value for the firm and, thus, firms can retain competitive advantage.

The number of benefits and costs of wage negotiations for a firm mentioned previously depends on the nature of search frictions. On the one hand, if search frictions are high for firms (they experience labor shortages and candidates are needed fast), a worker has many job offers, and the wage he expects to get increases. Firms that offer one, fixed wage will lose productive employees and they will go to bargaining firms. On the other hand, if search frictions are high for workers (unemployment is high or getting a job is difficult for other reasons), they will be willing to accept a lower wage. This means that even firms who post fixed wages will be able to attract productive employees and extract more value.

2.2. Empirical applications

Empirically, many researchers have also proven that firms vary in real life and choose different wage policies. Most have used probabilistic models (such as logit or probit) to look at the issue at hand: their main question is whether firms negotiate with their potential employees or not. Hall & Krueger (2012) use the logit model to exploit a survey of US workers and examine whether they agreed to the wage offer or bargained at the time of hiring. They find that factors such as gender, race, education level and working for a unionized or government job influence a worker's decision to bargain for their salary. Brenzel et al. (2014) arrive at similar conclusions. Unlike Hall & Krueger (2012), they possess data not only on individual workers but also on firm and job position characteristics, as they use data from the Germany Job Vacancy Survey. In 2011, they added a question to this survey of whether the firms negotiated with the applicant about their wages or not and used the logit model to study how prevalent wage bargaining is. They find that fixed wage posting is more popular in Germany and it is more prevalent for bigger firms, the public sector, part-time or fixed-term jobs as well as firms bound to collective bargaining agreements (Brenzel et al., 2014). In addition, wage bargaining is also more apparent for employees with higher education and jobs with special requirements.

Brenčič (2012) also looks at determinants of wage bargaining by using the probit model. In contrast to others, she uses job advertisement data in the UK, US and Slovenia, which is similar to ours in Latvia. She comes to comparable findings as Hall & Krueger (2012) irrespective of the differences in the data used. The validity of using job advertisement data for wage research is supported by Poeshcel (2018) who claims that advertised wages are similar to the actual wage workers receive. Also, Brenčič and Norris (2010) find that firms generally do not edit posted vacancy ads, meaning that a firm's intentions are stated clearly from the beginning when posting a job advert.

Importantly, Brenčič (2012) uses job ad data because firms may make the decision about simply offering a fixed wage or negotiations even before the interview process, i.e., already in the vacancy posting. She finds that firms vary not only in their decision to post or not to post wages at all, but also discovers that firms choose between advertising "negotiable, non-negotiable, approximate, minimum and maximum wage offers" (Brenčič, 2012, p. 1530), which can also be seen in our dataset.

Of considerable significance to our work, Brenčič (2012) also argues that the behavior of firms when posting a negotiable wage or a wage range (as opposed to a set, specific salary) is similar to a firm not posting a wage at all and expecting wage bargaining. She also finds that wider ranges in the offer reveal less about the job and in such cases, wages are more likely to be negotiated. Previous research by Andrews, Bradley and Upward (2001) supports these conclusions. Michelacci & Suarez (2006) further argue that firms who advertise a maximum wage (not a static one) are more inclined and open towards negotiation. All this evidence allows us to use the assumption that firms indicate their openness to salary negotiations already in the job ad by choosing to post a negotiable wage, such as a wage floor, ceiling, or a wage range.

A wage range in the job advert also implies bargaining from the job seeker's perspective. Leibbrandt & List (2015), while studying male and female behavior in salary negotiations, show that men will bargain for their wage more often than women in usual circumstances. Interestingly, when it is indicated that bargaining is possible, women will negotiate more than before and any differences between genders cannot be observed anymore. This shows that firms who imply possibilities to negotiate either explicitly or indirectly (by indicating a wage range) are expecting job seekers to bargain and are, thus, more open to negotiations.

2.3. Determinants of Wage Negotiations

In choosing the wage negotiation determinants, we follow the work of Brenzel et al. (2014). They are the ones who include firm side variables and deem them to be statistically significant factors. As our dataset gathers information from the company's perspective, we can apply their methods and chosen variables to investigate the same issue in Latvia.

Starting from the Mincer's earnings function (1974), which states that wage is determined by years of schooling and job experience, there has been an incredibly long list of researchers who have focused mainly on individual characteristics (e.g. age, gender, previous employment) in wage setting. However, Groshen (1991) finds that firm specifics are responsible for 20 - 70% of wage variation across industries. This is supported by Dickens and Katz (1987) and Gibbons and Katz (1992) who claim that wage differences arise to a large extent because firms are heterogeneous. Brenzel et al. (2014, p.42) find that firm-side characteristics are important for the choice between posting fixed wages and bargaining, specifically, they find that the frequency of wage negotiations is mostly associated with "establishment size, the collective bargaining status of the establishment, the type of job opening, and the state of the regional labor market".

As noted, we base most of our variables, such as occupations, industry, establishment size, part-time jobs and region specifications on the work by Brenzel et al. (2014). We add a profitability measure and look at ISCO classifications in contrast to Brenzel's (2014) required qualifications variable. In addition, we use dummy variables for regions instead of the regional unemployment rates. We exclude data on job level, fixed-term jobs and individual characteristics because of our dataset specifications and do not consider the collective bargaining status of the firm since there exist only a few industry-wide agreements, and wage negotiations are the most important at the company level in Latvia (Fulton, 2020). Next, we justify our choice of included variables and form their hypotheses:

- ***Occupations*** – Brenzel et al. (2014) find that the probability of wage bargaining increases with the level of qualification for the job – the higher the needed qualification, the more chance of extracting a higher wage from the company. In addition, they claim that in occupations where managerial or long-term experience is required, negotiations are more probable. Hall and Krueger (2012) state that almost all white-collar workers bargain while workers in blue-collar occupations negotiate for their wages very rarely. They also find that wage negotiations are rarer for inexperienced and less educated jobseekers (Hall & Krueger, 2012).

  For Latvia, European Commission (2020) projects that with the current higher education system, the supply of highly skilled professionals is becoming tighter. These Latvian labor market specifics point to a mismatch between supply and demand between high-level jobs and should result in more wage bargaining for highly skilled professions.

  We believe that **for highly skilled occupations, such as Managers, Professionals, as well as Technicians and associate professionals, wage negotiations are more likely to take place and wage ranges should be bigger.** The opposite should be true for low-skilled blue-collar professions, such as Elementary occupations or Plant and machine operators, and assemblers.

- ***Industry*** – Companies are often classified into industry types in any wage-related research. Brenzel et al. (2014) include the classification of economic activities in their paper. This is done mainly to see whether wage negotiations are used less in the public sector since compensation for civil servants is often determined by law or influenced by collective agreements. Brenzel et al. (2014) find that it is less common for public administration, education as well as defense and social security industry firms to allow wage bargaining.

  Dickens and Katz (1987) find that industry effects can explain 6.7% - 30% of wage variation even after including individual characteristic and location control variables. Gruetter and Lalive (2009) find that 74.2% of industry average wage variance is attributed to wage policies specific to industries. In addition, Haltiwanger, Scarpetta and Schweiger (2014) examine job flows in 16 economies, including Latvia, and find that industry effects explain the majority of variation in job flows, which refer to jobs created and destroyed. Our research will include dummy variables with the classification of economic activities in the form of NACE (The Statistical Classification of Economic Activities in the European Community) codes.

One mechanism through which industries might affect wage negotiations is worker productivity and scarcity. Michelacci and Suarez (2006) suggest that in markets, where the worker's productivity differs a lot and where there is a shortage of high productivity specialists, firms choose to bargain more. Indeed, the European Comission (2020) informs that in Latvia, employers are often dissatisfied with the supply of professionals in distinct industries, especially the Construction and Information and communication industries.

We hypothesize **that wage negotiations will be the most prevalent for the Construction as well as for the IT industries.**

- ***Establishment Size*** – Brenzel et al. (2014) include establishment size (measured as the number of employees) in their analysis of the prevalence of wage bargaining. They find that larger firms will negotiate less often due to internal labor markets, which implies hiring from within and firm-specific promotion procedures. Also, in larger companies, job responsibilities for different roles are more set-in-stone, since they are standardized for optimization. In addition, bigger firms might be less prone to negotiations as they have the opportunity to understand the market better before posting a fixed wage (Russo et al., 2000; Michelacci & Suarez, 2006). Adding to this, Sunday and Pfunter (2008) write that smaller firms usually are more flexible in their paying rates; they will base their wages on performance more than large firms because they have fewer restrictions by any formally accepted wage schemes.

We believe the notion that **the bigger the firm, the less probable the negotiations are. In addition, they will allow less bargaining in general (have smaller wage range offers).**

- ***Profitability*** – Meng (2004) mentions profitability as one of the factors that influence wage policy in the firm. Labor economists have tried to explain the correlation between a firm's wages and profitability with the rent-sharing hypothesis. Rent–sharing hypothesis implies that higher wages are demanded in higher profitability firms due to a higher possibility of wage bargaining: companies simply have more money to distribute to workers. Laborers should recognize this and extract higher wages from high-profitability firms. This is a sign of inefficient labor markets (Bigsten et al., 2003). We believe that the inclusion of this variable will give us deeper insights that have not been previously empirically investigated in similar research.

We hypothesize that **more profitable firms will allow for more negotiations and be more open to negotiations.**

- ***Region*** – Brenzel et al. (2014) write that the regional labor market role is important as it impacts the availability of other employment options and bargaining power of jobseekers and firms. They find highly statistically significant results for the negative effect of the regional unemployment rate on the probability of wage bargaining. However, they do not claim a causal effect between the two variables as they do not include other regional effects that may be correlated with the regional unemployment rate.

Regional differences are also a widely researched variable when looking at wage differentials, for example, Görzig, Gornig and Werwatz (2008) find substantial differences between what firms pay in Eastern and Western Germany. While investigating wage policies of two firms located in different countries but administered by the same group of people, Grund (2005) finds substantial differences, indicating that wage-setting strategies are affected by the institutional environment.

In our research, we are also able to classify job ads according to statistical regions of Latvia (Rīga, Pierīga, Vidzeme, Kurzeme, Zemgale, Latgale) and since there are major economical differences across these regions (e.g., GDP per capita, unemployment rate, population) we include region dummy variables as one of the determinants for wage bargaining. We use dummy variables instead of regional unemployment rates to better control for all effects associated with regions. Dmitrijeva (2008) also adds that the labor markets in Latvia themselves have substantial differences; in particular, Eastern Latvia shows the lowest matching efficiency, meaning that vacancies get filled in slower than elsewhere.

In the case of Latvia, we believe that **wage negotiations will be most prevalent and wage ranges will be the largest in Rīga and Pierīga regions as the**

unemployment levels are the lowest in these regions[4]. In contrast, wages are likely to be negotiated less in the Latgale region.

- ***Part-time jobs*** – Brenzel et al. (2014) find that fixed wage posting is more prevalent for part-time jobs. They consider this to be "atypical employment" and say that firms should engage in fixed wage posting more to lower transaction costs associated with wage negotiations. They do not give any other theoretical justifications but find this variable to be a significant influencer in their analysis on fixed wage posting vs. bargaining.

We hypothesize that **firms will be more likely to post a fixed wage and wage ranges will be tighter for vacancies advertising part-time jobs.**

[4] Unemployment rates as of 2019: Pierīga – 4.0%, Rīga – 5.8%, Kurzeme – 6.2%, Zemgale – 7.0%, Vidzeme – 8.1%, Latgale – 11.0%. Age group: 15-64. (Central Statistical Bureau of Latvia, 2021).

3. Use of Online Vacancy Data

In this section, we first provide an introduction to the availability of wage data in Latvian online job vacancies, explain the advantages of using such data and discuss potential biases and their relevance in our setting.

In 2018, Latvia introduced the law that mandates the posting of wages for all vacancies (Labour Law 2018, s. 32), meaning that potential employees have information about their wage before the interview process. As explained previously, this may suggest to workers whether firms are likely to opt for bargaining or not and even to what extent. This is not always the case and the absence of such a law has significantly affected previous research. Hall and Krueger (2012) and Brenčič (2012) find that only a fraction of job seekers knew their future pay before application. As we have access to wages for each vacancy from the job portals, we can directly analyze our research problem: determinants of wage negotiations and fixed wage posting.

Furthermore, using a job advert dataset addresses several issues in wage-setting literature. Hall & Krueger (2012) mention that survey data about the matter can be too dependent on respondent's recollections about the situation and suggest looking at the employer's perspective as a further research topic. Kurekova, Beblavy, Thum-Thysen (2013) state that using job ads avoids the bias created when only a selective group of people respond, which is typical for survey-based research, allowing us to have a more representative outlook. Brenzel et al. (2014), on which we base most of our theoretical and methodological work, add that one of the limitations of using survey data is that they only know what happens to the people that got the employment. Their main concern is not knowing whether wages were originally promoted as negotiable or fixed (Brenzel et al., 2014). Because of the law that mandates wage posting in advertisements, this information is available in Latvia.

Academia points to many advantages of using online data in labor economics research. Researchers claim that predictions about unemployment are significantly improved when web data is included in the analysis (D'Amuri and Marcucci, 2009; Fondeur and Karame, 2013). Deming and Kahn (2018) find that data collected from job ads on skills has more explanatory power than that available in labor market survey data. Lovaglio, Mezzanzanica and Colombo (2020) find that web job portal data share time-series characteristics with official data. A high degree of cointegration between labor market survey data and web data allows to use web data accurately and has the advantage of being always available and having additional information.

Nevertheless, researchers warn about potential biases in using such data. For example, employers will most likely post job ads online to target those audiences that will, in fact, look for a job online. This may lead to blue-collar jobs being underrepresented in the data as more educated workers are more likely to look for a job ad online (Carnevale et al., 2014). On the other hand, research by Brenčič (2012) finds that when given a chance to post or not to post the wage rate in an online job ad, employers post wage rates more if they are looking for lower-skilled workers. This makes the search process easier for firms – only people who are ready to work for the posted wage will apply, there is no need to spend time on wage negotiations and work can be started immediately. The most notable limitation to note, however, is that in Latvia, employees for managerial positions are usually not sought out on public job portals but rather through head-hunting and consulting firms and may add to some data biases (Cedefop, 2019).

However, Kurekova et al. (2013) claim that if there is a dominant job ad portal in a country, it can be considered to be representative of the labor market. In Latvia, the State Employment Agency vacancies are considered to comprise the majority of job opportunities and the online vacancy market is highly concentrated (Cedefop, 2019). Also, our dataset includes information from most job portals that can be found, including private job vacancy sites (such as CV-Online), where more of managerial and ICT specialist roles can be found (Cedefop, 2019). In addition, Latvians use the services provided by private job portals, such as CV-Online, extensively and value the advantages it provides, such as ease of use and saving time and financial resources (Blumberga & Kristberga, 2010).

Overall, lengthy and huge surveys might not be as informative as it seems, while job ad data can be considered more relevant and up to date. This is so because it shows the current sentiment in the labor market, and "uniqueness and richness of this data can nevertheless be exploited to inform policies in various fields" (Kurekova et al., 2013, p.1).

4. Data

Our main dataset on job ads, which includes information on job title, company, address, wages, wage type and information about part-time status, is extracted from five online vacancy posting portals: cv.lv, cvmarket.lv visidarbi.lv, teirdarbs.lv and the website of State Employment Agency of Latvia. All websites on the first two pages from a simple Google search were evaluated as potential candidates for data extraction. Keywords used in the search included “Latvia” and “vacancies”. Some of the websites have been excluded from the analysis as wage extraction is not a straight-forward procedure – wages are not shown in the preview of the ad. However, we believe that including these websites would not add much to our analysis (Appendix A).

Data gathering is done using Power BI’s function for web data extraction. This data is then cleaned, made uniform, duplicates, ads for jobs abroad and internships are removed. Latvian law dictates that all wages in job advertisements must be posted in their gross amount, thus, we assume that wages analyzed are gross wages (Labour Law, 2018). However, some positions are still advertised in their net wage amount and they are removed for simplicity. After these simple data manipulations, our dataset is comprised of 8963 observations that are posted from November 2020 to January 2021.

First, job titles are classified according to 2-digit ISCO (International Standard Classification of Occupations, 2012) codes to allow for a systematic analysis (Appendix B). This is done by making use of the fuzzy merge option in Power BI as well as manual matching for the vacancies that are too distinct for the program to recognize them. Next, we use Bureau van Dijk's Orbis to enhance our dataset by adding company-level information. The information we use includes company size measured by employee count, industry codes, and profitability margin. NACE (Nomenclature of Economic Activities) industry codes are added and linked to the company dataset, and afterward to the vacancy dataset (see NACE codes in Appendix C). Finally, all locations of job vacancies are classified into Statistical Regions of Latvia (Rīga, Pierīga, Latgale, Kurzeme, Zemgale, Vidzeme). For the overall view of how we link datasets, please see Appendix D.

After combining vacancy with company data available on Orbis we arrive at 8030 usable data entries (the difference arises from some companies not having employee count or profitability data and government agencies not having this data on Orbis at all). From this data amount, we can see that our dataset is not only applicable for research in the online job vacancy market, but also in the whole private Latvian labour market. Central Statistical Bureau states (2020a) that, on average, there were 11 698 vacancies in 2020 in the private sector and our dataset comprises 68.64% of this number. For numerical values (profit margin, employee count and wage range), we make use of a common approach in econometrics: values that are larger than the 99th percentile and smaller than the 1st percentile are considered to be outliers and removed from the dataset. After removing outliers, our dataset consists of 7395 usable values.

Next, we consider Brenčič's (2012) claim that when the posted wage ranges are very small and narrow, the wages can be considered to be non-negotiable. Thus, we reclassify those wages whose ranges are smaller than 10% to be fixed, non-negotiable wages. The representation of our data by advertised wage types can be seen in Table 1.

Advertised Wage Type	Count of Observations	Relative weight
Non-negotiable Wage	**2353**	**31.82%**
Fixed Wage	2353	31.82%
Negotiable Wage	**5042**	**68.18%**
Wage Range	3247	43.91%
Minimum Wage	1706	23.07%
Maximum Wage	89	1.20%

Table 1. Observation Count per Advertised Wage Type.

We can already gain some insights just by inspecting our data - in Latvia, 68.18% of wages are negotiated (Table 1). According to Brenzel et al. (2014), in Germany, 38% of wages were negotiated while Hall & Krueger find this number to be 37% in the U.S. This may imply that employers negotiate with their potential employees in Latvia more. In addition, we can see that the extent of wage bargaining is different in various industries and occupations – only 40% of wages are negotiated in the Arts, entertainment and recreation industry while in the Information and communication industry it reaches 87.75%; likewise, 56.49% of Elementary occupations jobs are negotiated while 77.13% of professionals engage in wage bargaining (Appendix E).

In our dataset, Business and administration professionals, Information and communications technology professionals and Sales workers have the most observations. Industries that are represented the most are Information and communication, Manufacturing, Wholesale and retail trade; Repair of motor vehicles and motorcycles. Detailed observation count for occupations and industries as well as regions can be found in Appendices E and F whereas summary statistics for numerical variables are presented in Appendix G.

5. Methodology

In this section, we first explain the implications of our chosen dataset for the models. We continue by introducing our methodological approaches – the logit and tobit models. Lastly, we briefly outline the intended methodology for robustness checks.

5.1. Data Implications

Although our unique dataset will provide us with novel insights into the topic of wage setting, it is cross-sectional, thus, limiting the possible data analysis methods that we can use to estimate the effects on variables. This means we will also not be able to use such techniques as a panel regression with time and entity fixed effects, which could help us account for possible biases in our data, so the results rely on the theoretical justification in the literature review section.

However, it must also be noted that online vacancy data may not be suitable for panel data just yet. Carnevale et al. (2014) explain that this is so due to data, such as statistics of ads themselves and the website visitation monthly frequency, being extremely volatile. Thus, labor market demand and job vacancy posting variation are difficult to distinguish from one another. Another problem is that the historical data amount is quite limited, almost non-existent in Latvia. In addition, consistency is the key for successful trend analysis. As technology and technological awareness in the country advances, the number of online job ads may increase as a result of that and not due to real labor market changes.

5.2. Logit Regression

Researchers (Brenzel et al., 2014; Hall & Krueger, 2012; Brenčič, 2012) have used probabilistic models to tackle a research question similar to ours. Thus, we also start our analysis by employing the logit model and add to existing research by examining whether firms post a set wage or a wage range on their job opening advertisements in Latvia. For the logit model, we classify all vacancies as having negotiable and non-negotiable wages. Negotiable wages include wages with starting salaries, maximum salaries, and wage ranges, whereas non-negotiable wages include wage postings with one exact number. We assume that if a firm is open to negotiations, it will indicate this in the job ad: a firm will opt for mentioning a flexible wage (e.g. starting wage) rather than writing one number with no additional information. We follow the general approach of Brenzel et al. (2014) and Stock & Watson (2019) in employing a logit regression:

$$\Pr(Y_i = 1|X_{1i}, X_{2i}, \dots, X_{ki}) = F(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}) \quad (1)$$

Here, *Y* refers to a dummy variable that equals 0 if the firm posted a set wage in the vacancy listing and 1 if it advertised a non-exact wage (wage range, wage floor, wage ceiling). *Pr* refers to the probability that *Y* equals 1 given X_k, which are our independent variables - firm size, industry, profitability and vacancy region, occupation, part-time variable. For the regressors referring to industry, region and occupation we will construct dummy variables, following Stock and Watson (2019), as they do not refer to numerical data. We also create factor variables for bins of company sizes as per Brenzel et al. (2014). Establishment size groups and observation counts can be seen in Appendix H. For the logit model, we employ marginal effects, which have broader economic implications and show us the change in the probability of company posting a negotiable wage given a unit change in X_k; this method is also used by Brenzel et al. (2014).

5.3. Tobit Regression

One reason why Brenzel et al. (2014) employed a logit regression is that their main variable of interest was binary – the survey that they used had a *yes/no* question of whether the firm bargained with its employees. At the end of her paper, Brenčič (2012) raises the study of the determinants of a job advert's wage range as a topic of further research. Because we have numerical wage range data from the job ads, we are also able to follow her suggestions and add to the existing literature by employing a tobit analysis and look for the determinants of the wage range. We use the relative wage range for this purpose and calculate it in percentage according to this formula:

$$Wage\ Range_i = \frac{Wage\ Ceiling_i - Wage\ Floor_i}{Wage\ Floor_i} * 100 \quad (2)$$

Wage floor and ceiling refer to the lower and upper bounds of the posted wage range; for example, if the wage is posted as *700-1000,* then the wage floor is *700* while the wage ceiling is *1000*.

A point to keep in mind is that wage range data is unique because its value cannot go below zero. This is called a censored value and is the reason why we cannot use a simple regression such as OLS. To examine the extent of the wage range, i.e., how open to wage negotiations a firm is, we will construct a Tobit model as per Stock and Watson (2019) and Wooldridge (2012):

$$Y_i^* = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i \tag{3}$$

Y^* is what is called a *latent variable*, while Y is our observed wage range. Y is identical to Y^* if $Y^* \geq 0$ and Y takes the value of zero when Y^* is zero or negative. The Tobit model estimates the densities of Y in cases when Y^* is (1) positive, (2) zero, (3) negative and uses them to construct a log-likelihood function. The coefficients for β are estimated, when solving for the maximum log-likelihood function (Stock & Watson, 2019; Wooldridge, 2012). We can interpret the β's as the percentage point change in the wage range[5], given a unit change in X_k. X_k refers to our independent variables (firm size, industry, region, profitability, occupation and whether the position is part-time). Here as well we will construct dummy variables for the non-numerical regressors as well as firm size as we did for the logit regression. In addition, u refers to the error term.

5.4. Robustness

Adding to the strength of our findings, we will perform several robustness checks. First, we will try to redefine the cutoff point when a wage range is too narrow for the wage to be considered negotiable. Then we will use an OLS regression for the part of our analysis where we consider the determinants of wage ranges:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i \tag{4}$$

where Y is the relative wage range in one vacancy listing, X_k refers to our independent variables and u is the error term.

We expect the findings to be similar when employing an OLS model due to our large sample size. In addition, Banfi and Villena-Roldán (2019) too use an OLS regression when analyzing cross-sectional job advert data. In similar research, Bronars & Famulari (1997) and Mccue et al. (1996) also make use of OLS regressions with wage growth data to investigate what determines the extent of wage growth. So, we believe this additional analysis will add to the robustness of our results.

[5] Wage ranges are measured in percentages, as portrayed in equation 2.

As our hypotheses about occupations states that negotiations are more prevalent and wage ranges wider for highly skilled occupations, we perform regressions where we divide all occupations into highly skilled (Managers, Professionals, Technicians and associate professionals) and low-skilled (all other groups) (International Standard Classification of Occupations, 2012). This lets us better understand the effect of highly skilled occupations, as we compare them to a much larger group, whereas in our original regressions the reference group is Elementary occupations against which all other occupations are more likely to negotiate.

Moreover, we also test different specifications of our models to test how sensitive the findings are to our assumptions. Previously, we assumed that wage ranges below 10% should be classified as fixed wages as opposed to negotiable. We look at a 5pp interval and test our results when we change the assumption to 7.5% and 12.5%. In addition, we examine interaction variables between company size and profitability, as well as quadratic functions.

6. Results

In this section, we firstly present the results of our logit regression and look at determinants of wage negotiation probability increases. Next, we introduce the findings from the tobit regression and explain the effect of our chosen variables on the wage range. Finally, we provide robustness check results. All regression results are summarized in tables, and in Appendix I, we summarize whether we find proof for our hypotheses established in the Literature Review.

6.1. Logit Results

To analyze what increases the probability of wage negotiations, we employ a logit regression. We present the marginal effects coefficients in Table 2, adding more explanatory variables with each iteration. The first column represents the regression only with occupations (ISCO-08), the second adds industries (NACE), the third includes numerical variables, such as company size and profitability, column four adds regions and lastly, part-time jobs are considered.

When comparing with the base occupation of *Elementary occupations*, which includes jobs like cleaners and helpers, agricultural, forestry and fishery laborers and other low skilled blue-collar professions, all other occupational groups are more likely to have negotiable wages posted in the adverts. Most occupation groups are also statistically significant and do not change drastically when adding new variables. This finding supports our hypothesis that highly skilled employees are more likely to bargain for their wage.

For *industries*, the base variable is Financial and insurance activities. Compared to it, all other industries are less prone to negotiate. Most variables stay statistically significant when including more factors, however, coefficients for Electricity, gas, steam and air conditioning supply and Information and communication industries are not statistically significant. We see that the lowest coefficient is for the Arts, entertainment and recreation industry – wages are 40.9pp less likely to be negotiated than in the Financial and insurance activities industry. The Mining and quarrying industry shows positive coefficients, but we do not take this into account for our analysis due to having only three observations for this industry. The results partially support our hypothesis – The Information and communication industry can be considered to be similar to Financial and insurance activities, the difference between them being statistically insignificant. However, the Construction industry, contrary to our initial belief, is not among the industries that negotiate about their wages – it is by

25.2pp less likely to post negotiable wages than the Financial and insurance activities industry.

By looking at *company size*, we find some proof for our hypotheses. Previously, we stated that larger companies will allow for less negotiations. We find evidence that companies with 50-199 employees and very large companies with more than 500 employees do negotiate less than very small companies, however, for other sizes, results are not statistically significant. Next, we find that results for the *profitability* measure are statistically insignificant and we cannot claim that more profitable companies are more likely to allow for wage bargaining; the result is not in line with our hypothesis.

In the fourth column, we add *region* variables to the regression. We find that compared to Rīga, other regions are more prone to wage negotiations, except for Latgale, where fixed-wage posting is more probable. For Kurzeme (15.8pp more likely to negotiate than Rīga), Vidzeme and Zemgale, the coefficients are statistically significant, but for Latgale and Pierīga they are not. Thus, we do not find support for our hypothesis that firms in Rīga will negotiate more. Finally, we see that the results for *part–time indication* in the job ad are statistically insignificant, and we cannot claim that companies will be more likely to post fixed wages for part-time jobs.

	Logit Coefficients (Marginal Effects)				
Regressor:	(1)	(2)	(3)	(4)	(5)
Managers	0.117*** (.038)	0.103*** (.036)	0.108*** (.036)	0.125*** (.036)	0.123*** (.036)
Professionals	0.206*** (.020)	0.137*** (.021)	0.140*** (.021)	0.157*** (.021)	0.155*** (.021)
Technicians and associate professionals	0.127*** (.024)	0.095*** (.024)	0.097*** (.024)	0.111*** (.024)	0.110*** (.024)
Clerical support workers	0.037 (.032)	0.001 (.032)	0.007 (.032)	0.019 (.032)	0.018 (.032)
Service and sales workers	0.120*** (.025)	0.091*** (.025)	0.098*** (.025)	0.096*** (.026)	0.095*** (.026)
Skilled agricultural, forestry and fishery workers	0.102 (.073)	0.065 (.072)	0.058 (.073)	0.049 (.075)	0.048 (.075)
Craft and related trades workers	0.064*** (.023)	0.058*** (.022)	0.056*** (.022)	0.057*** (.022)	0.055** (.022)
Plant and machine operators, and assemblers	0.040 (.026)	0.046* (.025)	0.043* (.025)	0.037 (.025)	0.036 (.025)
Agriculture, forestry and fishing		-0.130*** (.047)	-0.135*** (.046)	-0.169*** (.048)	-0.169*** (.048)

Mining and quarrying	0.147*** (.029)	0.143*** (.028)	0.142*** (.028)	0.142*** (.028)
Manufacturing	-0.173*** (.031)	-0.178*** (.031)	-0.193*** (.031)	-0.193*** (.031)
Electricity, gas, steam and air conditioning supply	-0.007 (.076)	0.004 (.071)	-0.018 (.078)	-0.018 (.078)
Water supply; sewerage, waste management and remediation activities	-0.208*** (.067)	-0.187*** (.065)	-0.188*** (.064)	-0.188*** (.064)
Construction	-0.244*** (.034)	-0.251*** (.034)	-0.251*** (.034)	-0.252*** (.034)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.178*** (.032)	-0.175*** (.032)	-0.173*** (.031)	-0.173*** (.031)
Transportation and storage	-0.281*** (.036)	-0.273*** (.036)	-0.266*** (.035)	-0.264*** (.035)
Accommodation and food service activities	-0.242*** (.055)	-0.258*** (.056)	-0.249*** (.055)	-0.247*** (.055)
Information and communication	0.003 (.031)	-0.008 (.031)	-0.003 (.030)	-0.003 (.031)
Real estate activities	-0.253*** (.052)	-0.263*** (.052)	-0.264*** (.052)	-0.264*** (.052)
Professional, scientific and technical activities	-0.128*** (.035)	-0.140*** (.035)	-0.137*** (.035)	-0.137*** (.035)
Administrative and support service activities	-0.188*** (.035)	-0.200*** (.035)	-0.195*** (.035)	-0.195*** (.035)
Human health and social work activities	-0.279*** (.038)	-0.266*** (.039)	-0.263*** (.038)	-0.262*** (.038)
Arts, entertainment and recreation	-0.443*** (.130)	-0.428*** (.132)	-0.408*** (.132)	-0.409*** (.132)
Other service activities	-0.176** (.093)	-0.189** (.095)	-0.173* (.092)	-0.173* (.092)
Company size 20-49		0.002 (.017)	-0.01 (.016)	-0.010 (.016)
Company size 50-199		-0.019 (.016)	-0.026* (.015)	-0.026* (.015)
Company size 200-499		0.023 (.018)	0.014 (.018)	0.014 (.018)
Company size 500+		-0.052*** (.018)	-0.053*** (.018)	-0.053*** (.018)
Profit margin		0.000 (.001)	0.001 (.001)	0.001 0.001
Pierīga			0.014 (.017)	0.015 (.017)
Kurzeme			0.158*** (.019)	0.158*** (.019)
Zemgale			0.094*** (.019)	0.095*** (.019)

Vidzeme	0.066*** (.023)	0.067*** (.023)
Latgale	-0.009 (.019)	-0.009 (.019)
Part-time		-0.024 (.038)

Note: The table presents the logit equation marginal effect coefficients that show the percentage point change in the probability for a firm to post a negotiable wage in the job advert, given a unit change in the independent variables. The dependent variable equals 1 if a negotiable wage is posted and 0 if a fixed wage is posted. Regression (1) is specified by using only ISCO job type variables. (2) includes NACE industry classifications, (3) adds company employee count and profit margin regressors. (4) introduces region dummies and (5) adds the part-time variable. Marginal effects are based on their mean for the numerical variables (*Profit margin*: 5.97%) and the reference group for factor variables (*Job type:* Elementary occupations; *Industry:* Financial and insurance activities; *Size:* Company size <20; *Region:* Rīga; *Part-time:* equals 1 if the position is part-time and 0 if full time). Standard errors of coefficients are given in parentheses. ***, ** and * mark significance at 1%, 5% and 10% levels.

Table 2. Logit regression results.

6.2. Tobit Results

We continue our analysis by employing a Tobit regression to investigate the determinants of the amount of the wage range for companies who negotiate. We present the results in Table 3. We run five specifications of the regression and include more explanatory variables each time in a similar manner to our logit analysis described in section 5.1.

All the *occupations* show positive coefficients, and all are significant when compared to Elementary occupations. The highest coefficient can be observed for Professionals (31.99pp), followed closely by Managers (31.41pp). This comes to no surprise, as exactly these two types of professions require the highest education levels and skills. Plant and machine operators, Craft and related trade workers as well as Clerical support workers all have the smallest significant coefficients, with 10.93pp, 11.19pp and 12.12pp, respectively. This supports our hypothesis that highly skilled occupations have a larger wage range while the lower-skilled ones have the narrowest spreads.

Almost all *industry* coefficients are negative – Arts, entertainment and recreation industry has the lowest coefficient and has by 87.73pp narrower wage ranges than the Financial and insurance activities industry. Only the Information and communication industry has a positive coefficient, however, it is insignificant, leading us to believe that there are no statistically significant differences between Financial and insurance activities and Information and communication industry. The mining and quarrying industry also has insignificant coefficients. In the end, we find support for our hypothesis that the Information and communication industry has the widest wage range (alongside with Financial and insurance activities industry). However, we do not find any evidence to our hypothesis that the construction industry has a wider wage range.

The findings about the *company size* are also in line with our hypothesis - larger companies will have more bargaining power and post narrower wage ranges. However, the results are only true for very large companies. Companies with more than 500 workers have by 8.41pp narrower wage ranges when compared to companies with less than 20 employees. In addition, we find that companies smaller than that (200-499 workers), will, in fact, negotiate more than very small companies.

Contrary to our expectations, we cannot see any effect on wage negotiations from firm *profitability* (more profitable companies should allow for more negotiations) and conclude that a firm’s profit margin has no significant influence on the wage range it will post in the job adverts. Next, we also do not find proof for the hypothesis that Rīga and Pierīga *regions* will have the widest wage ranges. Despite that, we find that Kurzeme and Zemgale have significant results and companies there post by 11.84pp and 7.37pp wider wage ranges in job adverts than those in Rīga, respectively. The last variable we look at is *part-time indication* and also here we do not find evidence that it will allow for less bargaining. The wage ranges for part-time positions are not statistically different from those that full-time positions have.

	Tobit Coefficients				
Regressor:	(1)	(2)	(3)	(4)	(5)
Managers	35.222*** (5.797)	30.173*** (5.517)	30.512*** (5.511)	31.376*** (5.529)	31.406*** (5.540)
Professionals	47.630*** (3.233)	31.047*** (3.239)	31.018*** (3.250)	31.965*** (3.296)	31.986*** (3.305)
Technicians and associate professionals	30.096*** (3.828)	22.559*** (3.698)	22.407*** (3.708)	23.099*** (3.738)	23.124*** (3.750)
Clerical support workers	19.430*** (4.887)	11.137** (4.727)	11.579** (4.738)	12.097** (4.754)	12.115** (4.760)
Service and sales workers	31.209*** (3.955)	23.693*** (3.909)	24.340*** (3.924)	24.155*** (3.927)	24.181*** (3.938)
Skilled agricultural, forestry and fishery workers	21.893* (11.214)	22.309** (10.765)	21.935** (10.736)	21.130** (10.754)	21.145** (10.756)
Craft and related trades workers	13.139*** (3.583)	11.345*** (3.423)	11.052*** (3.416)	11.159*** (3.423)	11.186*** (3.436)
Plant and machine operators, and assemblers	10.770*** (4.084)	11.862*** (3.949)	11.324*** (3.944)	10.905*** (3.946)	10.927*** (3.952)

Agriculture, forestry and fishing	-36.462*** (7.651)	-38.007*** (7.674)	-40.670*** (7.738)	-40.668*** (7.738)
Mining and quarrying	-1.961 (38.015)	-2.963 (37.902)	-2.670 (37.882)	-2.644 (37.883)
Manufacturing	-32.750*** (5.138)	-34.857*** (5.255)	-36.048*** (5.294)	-36.038*** (5.295)
Electricity, gas, steam and air conditioning supply	-32.308** (13.921)	-28.281** (13.897)	-31.211** (13.897)	-31.203** (13.897)
Water supply; sewerage, waste management and remediation activities	-49.975*** (10.301)	-46.457*** (10.309)	-46.784*** (10.298)	-46.795*** (10.298)
Construction	-37.408*** (5.499)	-38.897*** (5.586)	-39.236*** (5.588)	-39.230*** (5.589)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-30.463*** (5.130)	-30.125*** (5.286)	-30.254*** (5.290)	-30.257*** (5.290)
Transportation and storage	-47.656*** (5.752)	-46.734*** (5.857)	-46.483*** (5.866)	-46.506*** (5.871)
Accommodation and food service activities	-37.957*** (8.188)	-41.177*** (8.381)	-41.077*** (8.376)	-41.129*** (8.393)
Information and communication	9.996* (5.087)	6.384 (5.206)	6.980 (5.202)	6.980 (5.202)
Real estate activities	-57.313*** (8.199)	-59.577*** (8.264)	-60.158*** (8.260)	-60.161*** (8.260)
Professional, scientific and technical activities	-26.431*** (5.573)	-28.143*** (5.727)	-28.290*** (5.721)	-28.285*** (5.721)
Administrative and support service activities	-26.674*** (5.512)	-28.582*** (5.633)	-28.569*** (5.629)	-28.576*** (5.630)
Human health and social work activities	-65.781*** (6.133)	-63.851*** (6.246)	-63.152*** (6.289)	-63.169*** (6.292)
Arts, entertainment and recreation	-90.289*** (24.437)	-88.372*** (24.504)	-87.731*** (24.485)	-87.725*** (24.485)
Other service activities	-21.640 (13.633)	-22.999* (13.725)	-21.676 (13.737)	-21.667 (13.737)
Company size 20-49		2.033 (2.511)	1.540 (2.516)	1.545 (2.517)
Company size 50-199		0.874 (2.359)	0.136 (2.364)	0.139 (2.365)
Company size 200-499		8.212*** (2.604)	7.076*** (2.632)	7.082*** (2.633)
Company size 500+		-7.846*** (2.785)	-8.408*** (2.796)	-8.405*** (2.796)
Profit margin		0.050 (.071)	0.059 (.071)	0.059 (.071)
Pierīga			1.664 (2.709)	1.660 (2.709)
Kurzeme			11.848*** (3.568)	11.837*** (3.570)

Zemgale	7.384** (3.300)	7.371** (3.304)
Vidzeme	2.055 (3.860)	2.036 (3.866)
Latgale	-3.930 (3.100)	-3.941 (3.102)
Part-time		0.538 (6.072)

Note: The table presents Tobit equation coefficients. The dependent variable is the percentage amount of the relative wage range. Coefficients represent percentage point change in the wage range. Regression (1) is specified by using only ISCO job type variables. (2) includes NACE industry classifications, (3) adds company employee count and profit margin regressors. (4) introduces region dummies and (5) adds the part-time variable. Reference groups: *Job type:* Elementary occupations; *Industry:* Financial and insurance activities; *Size:* Company size <20; *Region:* Rīga; *Part-time:* equals 1 if the position is part-time and 0 if full time. Standard errors of coefficients are given in parentheses. ***, ** and * mark significance at 1%, 5% and 10% levels.

Table 3. Tobit regression results.

6.3. Robustness Results

When changing the cutoff point for when a wage range is too narrow for the wage to be considered negotiable (from 10% to 7.5% and 12.5%), the results stay in line with our findings from logit and tobit models. In addition, the inclusion of interaction variables or quadratic function does not alter our main conclusions as well. The only significant interaction variable we find is between company size and profitability, indicating that profitability might increase bargaining for large firms. Additionally, the general results are similar when employing an OLS regression model instead of Tobit (all results can be seen in Appendix J).

When looking at occupations, instead of Managers and Professionals as in the tobit regression, the highest coefficients can be observed for Skilled agricultural, forestry and fishery workers who have by 20.6pp wider wage ranges relative to Elementary occupations. This indicates potentially higher bargaining power, as these kinds of workers are scarce in the market, as they are not simple laborers and need specialty education. However, the coefficient might also be exaggerated due to there being only 30 observations in our dataset for this group (Appendix E). The second highest coefficient is for Service and sales workers who have a 14.2pp larger wage range than Elementary occupations workers. This might be due to service and sales workers including such occupations as cashiers who often receive minimum salaries as well as sales representatives working on commission. They are followed by Managers and Professionals with 9pp and 8.3pp wider wage ranges than Elementary occupations, respectively.

For industries, coefficients for Arts, entertainment and recreation industry, Accommodation and food service activities as well as Administrative and support service activities turns insignificant when compared to tobit regression while the Information and communication industry has a positive significant coefficient. However, this does not alter our main findings.

As for our division of occupations into two groups – highly skilled and low-skilled –, we find that low-skilled occupations are by 9.51pp less likely to engage in wage negotiations (logit model) and have by 17.22pp narrower wage ranges (tobit model) when compared to highly skilled occupations (Appendix K). These additional results validate our findings about occupations in the main regressions.

7. Discussion

In this section, we provide a theoretical context for our empirical results, mainly basing our findings on research already discussed in the Literature Review. We try to direct the reader to the link between several economic factors and wage negotiations vs. fixed wage posting. Lastly, we point to the limitations of our work and suggest further research ideas.

7.1. Discussion of Results

In general, our findings regarding *occupational groups* are in line with other researchers – Brenzel et al. (2014), Hall and Krueger (2012) and Brenčič (2012) all have stated that for occupations where higher qualifications and more sophisticated skills are needed, wage negotiations are more likely to take place. We add that companies seeking highly skilled professionals and managers are also more likely to allow for more wage negotiations (spreads are wider). This finding is also verified in our robustness check, where we divide occupations into highly skilled professionals and low-skilled professionals according to ISCO-08 guidelines and find that low-skilled occupations are less likely to negotiate and have lower wage ranges (Appendix K). The results might also be amplified by the current Latvian job market conditions, where employers are often dissatisfied with the supply of highly skilled professionals (European Commission, 2020).

The implication of this is that employers who are seeking to attract workers with higher qualifications are likely to lose out on productive workers if they post only one fixed wage. To attract suitable employees, firms should post flexible wages (e.g., wage ranges or wages that start from a specific amount). In addition, workers who have acquired higher levels of education and possess a sophisticated skillset should look for vacancies with wage ranges in advertisements.

As most wage-related research has found, *industries* in which a company operates in, have significant effects on wage structures, policies, amounts and negotiations (Dickens and Katz, 1987; Gruetter and Lalive, 2009; Haltiwanger et al., 2014; Brenzel et al., 2014). This is also the case in our results, with the Financial and insurance activities industry as well as the Information and communication industry being more prone to negotiations and having the widest wage ranges. Indeed, the European Comission (2020) reports that there is inadequate supply of Information and communications industry professionals in Latvia. In addition, Zhao et al. (2016) find support for substantial productivity variation in the Financial and insurance services sector.

In contrast to our hypothesis, we find no proof that workers in construction industry can negotiate more. An explanation for such finding might lie in the fact that since 2019, there is a collective bargaining agreement in the construction industry, which sets the minimum wage in this sector above the state's minimum wage as well as a 5% education aid paid on a monthly basis (Latvijas Būvniecības nozares arodbiedrība, 2019). Brenzel et al. (2014) state that engagement in collective bargaining agreements significantly lowers the prevalence of individual wage bargaining, thus, we have a firm reason to believe this explanation. Generally, findings about industries are in line with Michelacci and Suarez (2008) who state that wage bargaining is more common in industries with differing worker productivity and where high productivity professionals are scarce. This brings us to conclude that firms operating in industries with such characteristics should post flexible wage offers. In return, workers should expect to bargain for their wages in such industries as Information and communication and Financial and insurance activities in Latvia.

When looking at the *establishment size,* we find that large companies will negotiate less and have narrower wage ranges if they post such a wage when compared to smaller firms. Thus, our results match Brenzel et al. (2014). This is likely due to the ability of large firms to post more job ads and find an optimal wage to advertise (Russo et al., 2000). In addition, big companies are often bound by rigid salary structures, so negotiations for them, even if possible, are limited (Sunday and Pfunter, 2008). This finding implies that large firms might be able to extract value even when posting wages, however, the productivity of such firms is likely to be lower. For workers, it means that applying for a job in a large company will likely result in the wage that has been posted initially. However, when carrying out the tobit analysis, we find this result to be true only for very large companies with employee size of over 500. In fact, medium-size (200-499 employees) companies are prone to have wider wage ranges than very small companies. This may be due to medium-sized companies not yet having very inflexible wage policies, but this result could be investigated further by other researchers.

We find no support for the idea that more *profitable* firms will negotiate more and have wider wage ranges, as the results for this variable are insignificant in both regressions and the robustness check. We are led to believe that it is not a firm's ability to pay but rather the need to adapt to the market conditions that drives a company's decision to engage in wage negotiations with its employees (Michelacci & Suarez, 2006). In addition, we cannot support Bigsten et al. (2003) who claim workers should recognize that more profitable firms have more money and extract higher wages because of this. First, a firm's profitability is not easily attainable information for the average jobseeker, and our findings suggest that it would not make sense for them to seek this information out. Second, we cannot test this mechanism since we do not know how the workers will negotiate during the job interview as all our data is firm-side, and we are looking at what the company is communicating through its job ad.

Our results about *regions* are surprising – we do not find proof for our hypothesis that Rīga and Pierīga will negotiate the most and find that actually firms in Kurzeme, Zemgale and Vidzeme negotiate with their employees more than firms in Rīga. Hence, employees in these regions should not be afraid to engage in wage negotiations, even though they would be inclined to perceive their bargaining power as being lower. This belief may arise since they are outside the capital city of Rīga where most of the country's economic activity is centered. Furthermore, companies in Kurzeme post the widest wage ranges. These results should not arise because of issues with the sample, as the regional distribution of our data is in line with population data shown in Appendix F.

In contrast to Brenzel et al. (2014), who found that wage negotiations depend on regional unemployment level, we created dummy variables to control for various regional effects, however, it is certain that unemployment level still has an impact on the matter. When we were forming the hypothesis, we were relying on 2019 data about the unemployment rate and hypothesized that Rīga and Pierīga will experience the most negotiations as unemployment rates are the lowest. Table 4 shows us that the dynamic between regions has changed substantially in 2020 when we were extracting our job vacancies from the web. Now, Kurzeme and Zemgale regions actually have a lower unemployment than Rīga, and it is likely that our results are impacted by this. Another reason for such an outcome might be that Rīga is the economic center and powerhouse of the country – people in general and especially highly-skilled professionals move there to find jobs. This means that regions lose qualified specialists, and the labor market tightens. Thus, we again draw upon the mechanism proposed by Michelacci and Suarez (2006) – firms choose to negotiate to be able to hire more productive and better-qualified workers. However, this assumption should be explored in further research.

Region	2019	2020
Rīga	5.8%	7.9%
Pierīga	4.0%	7.0%
Vidzeme	8.1%	9.2%
Kurzeme	6.2%	7.7%
Zemgale	7.0%	7.8%
Latgale	11.0%	12.7%

Table 4. Unemployment rates in the statistical regions of Latvia in 2020 compared to 2019. (Central Statistical Bureau of Latvia, 2021).

We do not arrive at similar conclusions as Brenzel et al. (2014) regarding *part-time* jobs. In our analysis, part-time job adverts do not statistically differ from full-time job postings. However, this might arise from the fact that we only have 145 part-time observations comprising 1.96% of the whole dataset. In reality, 9.2% of the Latvian labor force are employed in part-time positions, indicating our sample is not representative with regards to this factor (Central Statistical Bureau of Latvia, 2019). Another reason for this might be that selection bias, which we mentioned previously, may be more of an issue for part-time jobs. As we see, job portals have very little part time vacancies and these kinds of jobs are often advertised more informally on social media (Facebook), local newspapers, other, less reputable advertisement websites (e.g., ss.lv) or by word of mouth in Latvia.

7.2. Limitations and Suggestions for Further Research

In spite of its novelty, it is important to acknowledge our dataset limitations. First, blue-collar jobs may be underrepresented in datasets gathered from online vacancies (Carnevale et al., 2014). However, as seen by the count of observations in Appendix E, blue-collar professionals, such as Elementary occupations or Plant and machine operators, and assemblers have a sufficient number of observations. In our situation, the underrepresented group might be Managers, who are usually recruited through headhunting (Cedefop, 2019). Part-time jobs and some industries can also be considered underrepresented in our dataset (Mining and quarrying; Art, entertainments and recreation; Other service activities). Next, it must be noted that occupation names extracted from job adverts are classified into 2-digit ISCO codes using mainly our own judgment and this may lead to discrepancies. Another limitation that has been pointed out to us concerns the fact that there is no way of knowing whether firms who post wage ranges will actually bargain and wider ranges allow for more wage bargaining.

As we have stressed throughout the paper, our research focuses on the firm-side intentions about wage negotiations at the time of posting the job vacancy. However, our findings may not always be representative of what happens during the actual wage negotiation process because there are two parties – the employer and the job seeker. As mentioned in the literature review, individual characteristics also have a notable influence on whether and to what extent will the wage be negotiated. Due to us using job vacancy data, we have no information about the individual job seekers.

We recognize that the methodological approaches used in our research have several limitations, for example, we do not look at fixed effects and do not add control variables. For further research, we suggest investigating this issue over a longer time period as well as more institutional environments and countries so that the benefits of panel analysis can be extracted, and findings can be more generalizable. In addition, researchers may find it useful to combine online vacancy dataset with survey data in order to know what happens from the beginning of employee search until the point of hiring and actual wage determination. Another idea is to look at what attributes of job ads do employees consider the most important in order to find additional drivers of wage negotiations.

8. Conclusion

By using the assumption that firms indicate their willingness to negotiate already in the job advertisements, we find that (1) the higher qualification is needed for a job, the more likely it is that firms will negotiate as well as be more open to bargaining, (2) industries with differing worker productivity and scarcity of professionals are more willing to negotiate wages, (3) large firms negotiate less, (4) negotiations are more likely to happen in Kurzeme, Zemgale and Vidzeme regions when compared to Rīga, (5) profitability of the firm and part-time status of the job are not important factors for wage negotiations from the firm's perspective.

Our findings aid in wage negotiation related research, have implications for a firm's productivity, costs and suitable employee attraction, as well as help employees understand whether firms are open to bargaining. In addition, we employ a novel online vacancy dataset, which provides up-to-date insights into the Latvian labor market and also shows that chaotic user input data into job vacancy portals can be made uniform and used for a deeper analysis. We believe that this type of approach would be useful for further labor economics research on wages. Furthermore, this dataset allows us to not only investigate whether firms are more likely to bargain or post non-negotiable wages, but also examine the extent of openness to negotiations using tobit analysis, which previous research has not attempted to investigate. In general, our findings are in line with already existing wage negotiation research, in spite of data differences and new methodology. The results stay robust when changing assumptions, including interaction and quadratic variables as well as when employing a different methodological analysis.

In further research, it would be valuable to look at the same problem over a longer period of time and other institutional environments to employ panel analysis. In addition, researchers could investigate the process of wage negotiations starting from the initial job vacancy advertisement and ending with recruitment as well as understand other drivers of wage negotiations from both employee and employer perspectives.

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10. Appendices

Appendix A. Websites and data summary

Excluded Websites	Reason for excluding
1188.lv/vakances	Cannot extract wages right away. Only puts together data from cv.lv and teirdarbs.lv
prakse.lv	Internships are not in the scope of this research. Wages can be extracted only for 25 job vacancies. Many vacancies are the same as in State Employment Agency of Latvia.
ss.com/lv/work/are-required/	Cannot extract wages right away. Also, would not be considered to be a reputable source.
kurdarbs.lv	Cannot extract wages right away.
workingday.lv/lv/vakances/visas-vakances/	Cannot extract wages right away. Very few vacancies.
irdarbs.lv/	Cannot extract wages right away. Most job ads are from nva.gov.lv
zip.lv/darbs-un-bizness/piedava-darbu	Cannot extract wages right away. Very few vacancies with mainly blue-collar low skilled jobs.

Table A.1. Excluded job vacancy websites.

Included websites	Count of Job Ads
cv.lv	2338
visidarbi.lv/darba-sludinajumi	1909
cvmarket.lv/darba-piedavajumi-kategorijas	373
teirdarbs.lv	42
cvvp.nva.gov.lv/#/pub/vakances/saraksts	2733

Table. A.2. Observation count from included job vacancy websites.

Appendix B. ISCO-08 Codes and Count of Observations

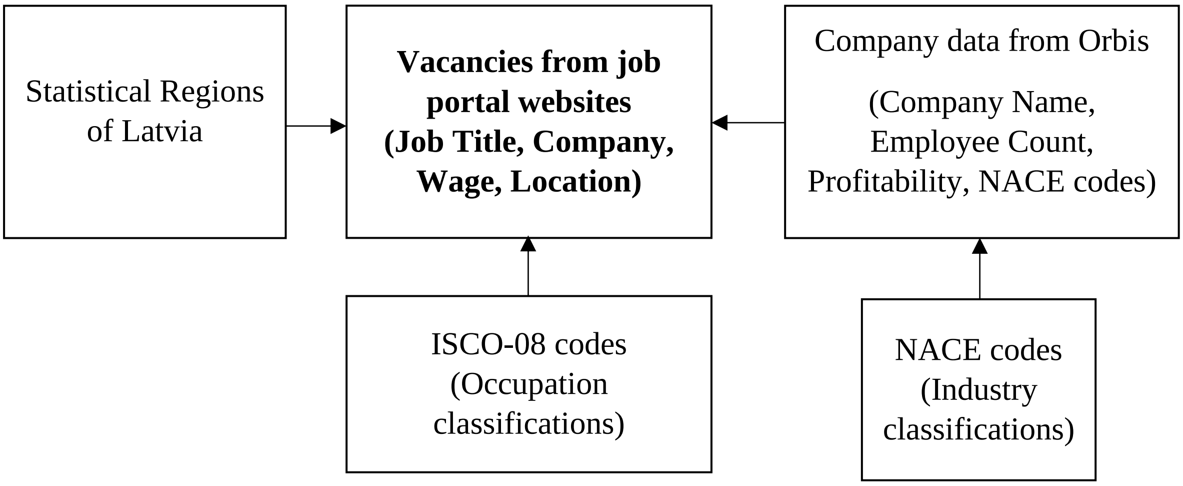
ISCO-08	Name	Count of observations
1	**Managers**	**195**
11	Chief executives, senior officials and legislators	10
12	Administrative and commercial managers	91
13	Production and specialized services managers	88
14	Hospitality, retail and other services managers	6
2	**Professionals**	**2549**
21	Science and engineering professionals	365
22	Health professionals	276
23	Teaching professionals	5
24	Business and administration professionals	1060
25	Information and communications technology professionals	709
26	Legal, social and cultural professionals	137
3	**Technicians and associate professionals**	**823**
31	Science and engineering associate professionals	204
32	Health associate professionals	79
33	Business and administration associate professionals	378
34	Legal, social, cultural and related associate professionals	36
35	Information and communications technicians	123
4	**Clerical support workers**	**349**
41	General and keyboard clerks	73
42	Customer services clerks	187
43	Numerical and material recording clerks	66
44	Other clerical support workers	23
5	**Service and sales workers**	**704**
51	Personal service workers	125
52	Sales workers	527
53	Personal care workers	0
54	Protective services workers	52
6	**Skilled agricultural, forestry and fishery workers**	**45**
61	Market-oriented skilled agricultural workers	15
62	Market-oriented skilled forestry, fishery and hunting workers	30
63	Subsistence farmers, fishers, hunters and gatherers	0
7	**Craft and related trades workers**	**1292**
71	Building and related trades workers, excluding electricians	439
72	Metal, machinery and related trades workers	435
73	Handicraft and printing workers	28
74	Electrical and electronic trades workers	183

75	Food processing, word working, garment and other craft and related trades workers	207
8	**Plant and machine operators, and assemblers**	**698**
81	Stationary plant and machine operators	288
82	Assemblers	52
83	Drivers and mobile plant operators	358
9	**Elementary occupations**	**740**
91	Cleaners and helpers	93
92	Agricultural, forestry and fishery labourers	62
93	Labourers in mining, construction, manufacturing and transport	324
94	Food preparation assistants	13
95	Street and related sales and service workers	0
96	Refuse workers and other elementary workers	248

Appendix C. NACE Classifications

NACE	Name	Count of observations
A	Agriculture, forestry and fishing	151
B	Mining and quarrying	3
C	Manufacturing	1601
D	Electricity, gas, steam and air conditioning supply	27
E	Water supply; sewerage, waste management and remediation activities	63
F	Construction	778
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	1342
H	Transportation and storage	594
I	Accommodation and food service activities	114
J	Information and communication	955
K	Financial and insurance activities	176
L	Real estate activities	125
M	Professional, scientific and technical activities	486
N	Administrative and support service activities	559
O	Public administration and defence; compulsory social security	0
P	Education	0
Q	Human health and social work activities	379
R	Arts, entertainment and recreation	15
S	Other service activities	27
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0
U	Activities of extraterritorial organisations and bodies	0

Appendix D. Linkage of Data



Appendix E. Observation Count for Negotiable and Nonnegotiable Wages

Major group ISCO-08	**Count of observations for non-negotiable wages**	**Count of observations for negotiable wages**	**Negotiable wage weight**	**Mean of Wage range**
Managers	62	133	68.21%	0.240
Professionals	583	1966	77.13%	0.303
Technicians and associate professionals	254	569	69.14%	0.208
Clerical support workers	139	210	60.17%	0.170
Service and sales workers	222	482	68.47%	0.236
Skilled agricultural, forestry and fishery workers	15	30	66.67%	0.203
Craft and related trades workers	480	812	62.85%	0.156
Plant and machine operators, and assemblers	276	422	60.46%	0.143
Elementary occupations	322	418	56.49%	0.105
Total	**2353**	**5042**	**68.18%**	**0.217**

Table E.1. Observation count for negotiable and nonnegotiable wages for ISCO-08 occupation codes.

NACE	Count of observations for non-negotiable wages	Count of observations for negotiable wages	Negotiable wage weight	Mean of Wage range
Agriculture, forestry and fishing	46	105	69.54%	0.152
Mining and quarrying	0	3	100.00%	0.189
Manufacturing	537	1064	66.46%	0.172
Electricity, gas, steam and air conditioning supply	4	23	85.19%	0.148
Water supply; sewerage, waste management and remediation activities	22	41	65.08%	0.106
Construction	320	458	58.87%	0.162
Wholesale and retail trade; repair of motor vehicles and motorcycles	440	902	67.21%	0.202
Transportation and storage	270	324	54.55%	0.111
Accommodation and food service activities	45	69	60.53%	0.181
Information and communication	117	838	87.75%	0.493
Financial and insurance activities	22	154	87.50%	0.380
Real estate activities	49	76	60.80%	0.110
Professional, scientific and technical activities	126	360	74.07%	0.233
Administrative and support service activities	187	372	66.55%	0.231
Human health and social work activities	150	229	60.42%	0.068
Arts, entertainment and recreation	9	6	40.00%	0.036
Other service activities	9	18	66.67%	0.283
Total	**2353**	**5042**	**68.18%**	**0.217**

Table E.2. Observation count for negotiable and nonnegotiable wages for NACE classifications.

Appendix F. Observation Count per Region of Latvia and Comparison with Population Data (Central Statistical Bureau of Latvia, 2020b)

Region	**Count of observations in job advert dataset**	**Weight in job advert dataset**	**Actual job vacancies on average per year**	**Weight in population data**
Rīga	4555	61.60%	11277	54.10%
Pierīga	822	11.12%	3913	18.80%
Kurzeme	421	5.69%	1487	7.10%
Zemgale	534	7.22%	1251	6%
Vidzeme	392	5.30%	1244	6%
Latgale	671	9.07%	1687	8.10%

Appendix G. Summary Statistics for Numerical Variables.

	Summary Statistics			
	Profit margin	Employee count	Wage range (all data)	Wage range (>0)
Mean	5.97	345.80	0.22	0.50
Median	4.41	79	0	0.40
St. dev.	11.65	710.01	0.34	0.36
Minimum	-46.32	2	0	0.10
Maximum	48.24	4468	1.97	1.97

Note: The table presents the descriptive statistics for the variables. Profit margin is given in percentage amount. Both wage range variables refer to relative wage range and are given in decimal amount. Wage range is calculated as the euro amount wage range (wage ceiling minus wage floor) divided by wage floor. The first wage range variable (all data) also includes observations where the wage range is zero, i.e., fixed wage, only starting or maximum wage. The second wage range variable presents statistics for the subsample with only a positive wage range.

Appendix H. Observation Count by Company Size Groups

Company Size	**Count of Observations**	**Percentage of Observations**
<20 employees	1796	24.29%
20-49 employees	1277	17.27%
50-199 employees	1811	24.49%
200-499 employees	1267	17.13%
500+ employees	1244	16.82%

Appendix I. Summary of Wage Negotiation Determinant Hypotheses (as in Literature Review) and Regression Results (as in Results).

Variable	Hypothesis	Logit	Tobit
Occupations	For highly skilled occupations, such as Managers, Professionals, as well as Technicians and associate professionals, wage negotiations are more likely to take place and wage ranges should be bigger. The opposite should be true for low-skilled blue-collar professions, such as Elementary occupations or Plant and machine operators, and Assemblers.	Yes	Yes
Industry	Wage negotiations will be the most prevalent for the Construction as well as for the IT industries.	Partially *("Yes" for IT, "No" for Construction)*	Partially *("Yes" for IT, "No" for Construction)*
Establishment Size	The bigger the firm, the less probable the negotiations are. In addition, they will allow less bargaining in general (have smaller wage range offers).	Partially *(Very large companies with more than 500 employees offer more negotiable wages)*	Partially *(Very large companies with more than 500 employees offer larger wage ranges, but companies with 200-499 workers are found to offer narrower wage ranges)*
Profitability	More profitable firms will allow for more negotiations and be more open to negotiations.	No	No
Region	Wage negotiations will be most prevalent and wage ranges will be the largest in Rīga and Pierīga regions as the unemployment levels are the lowest in these regions. In contrast, wages are likely to be negotiated less in the Latgale region.	No	No
Part-time status	Firms will be more likely to post a fixed wage and wage ranges will be tighter for vacancies advertising part-time jobs.	No	No

Note: Variable represents the potential determinant for wage negotiation prevalence or the openness to negotiation. Detailed explanations of variables and the hypothesis for each variable is proposed in the Literature Review section. The logit column indicates whether we have found proof of an increase or decrease in the probability for wage negotiations due to a change in a variable. Similarly, the tobit column shows whether we have found evidence for the effect of a variable on the wage ranges. The logit and tobit columns state "Yes" if we have found evidence for our hypothesis, "No" if we have found the opposite or insignificant results, and "Partially" if we have found some proof for the hypothesis.

Appendix J. OLS Regression Results (Robustness Check).

	OLS Coefficients				
Regressor:	(1)	(2)	(3)	(4)	(5)
Managers	10.724** (4.396)	6.617 (4.264)	8.403** (4.247)	8.869* (4.275)	9.036** (4.283)
Professionals	15.052*** (2.643)	5.747** (2.703)	7.470*** (2.704)	8.164*** (2.764)	8.277*** (2.770)
Technicians and associate professionals	6.392** (3.064)	1.085 (3.010)	2.785 (3.009)	3.380 (3.059)	3.505 (3.065)
Clerical support workers	5.937 (3.926)	1.632 (3.853)	3.980 (3.845)	4.486 (3.876)	4.531 (3.877)
Service and sales workers	16.646*** (3.203)	12.035*** (3.206)	14.203*** (3.206)	14.020*** (3.221)	14.172*** (3.230)
Skilled agricultural, forestry and fishery workers	19.925** (9.194)	21.531** (9.094)	21.331** (9.032)	20.588** (9.055)	20.553** (9.056)
Craft and related trades workers	8.395*** (3.003)	7.110** (2.904)	7.138** (2.885)	6.689** (2.909)	6.849** (2.920)
Plant and machine operators, and assemblers	5.712* (3.406)	6.898** (3.306)	7.069** (3.292)	6.647** (3.301)	6.826** (3.313)
Agriculture, forestry and fishing		-6.467 (5.668)	-10.484* (5.715)	-11.972** (5.779)	-11.970** (5.780)
Mining and quarrying		-18.817 (24.243)	-21.380 (24.120)	-20.856 (24.169)	-20.731 (24.172)
Manufacturing		-5.120 (3.359)	-9.326*** (3.515)	-10.308*** (3.561)	-10.238*** (3.563)
Electricity, gas, steam and air conditioning supply		-21.347** (9.547)	-17.212* (9.539)	-18.307* (9.553)	-18.296* (9.554)
Water supply; sewerage, waste management and remediation activities		-19.699** (7.829)	-17.598** (7.823)	-17.357** (7.825)	-17.490** (7.828)
Construction		-1.521 (3.655)	-5.634 (3.720)	-6.226* (3.747)	-6.200* (3.747)
Wholesale and retail trade; repair of motor vehicles and motorcycles		-2.944 (3.303)	-6.044* (3.474)	-6.321* (3.486)	-6.324* (3.486)
Transportation and storage		-11.989*** (4.017)	-13.886*** (4.120)	-14.040*** (4.139)	-14.146*** (4.143)
Accommodation and food service activities		0.163 (6.208)	-6.511 (6.371)	-5.991 (6.388)	-6.423 (6.425)
Information and communication		19.144*** (3.186)	13.963*** (3.316)	14.008*** (3.316)	14.030*** (3.317)
Real estate activities		-9.195 (6.440)	-15.083** (6.474)	-15.507** (6.485)	-15.457** (6.486)
Professional, scientific and technical activities		-1.780 (3.647)	-8.140** (3.810)	-8.214** (3.814)	-8.160** (3.816)
Administrative and support service activities		2.758 (3.643)	-3.259 (3.793)	-3.313 (3.797)	-3.314 (3.798)

Human health and social work activities		-25.244***	-23.230***	-24.366***	-24.473***
		(4.337)	(4.460)	(4.544)	(4.547)
Arts, entertainment and recreation		-30.578	-35.719	-34.804	-34.694
		(24.631)	(24.482)	(24.498)	(24.501)
Other service activities		24.433**	17.199	16.725	16.802
		(11.166)	(11.222)	(11.241)	(11.242)
Company size 20-49			-2.090	-2.031	-2.020
			(1.936)	(1.944)	(1.944)
Company size 50-199			-4.353**	-4.340**	-4.327**
			(1.812)	(1.831)	(1.831)
Company size 200-499			-1.568	-1.409	-1.377
			(1.918)	(1.948)	(1.948)
Company size 500+			-14.207***	-14.061***	-13.995***
			(2.167)	(2.185)	(2.188)
Profit margin			-0.037	-0.032	-0.032
			(.052)	(.052)	(.052)
Pierīga				0.178	0.173
				(2.100)	(2.100)
Kurzeme				5.894**	5.842**
				(2.759)	(2.760)
Zemgale				3.918	3.852
				(2.604)	(2.607)
Vidzeme				0.986	0.899
				(3.157)	(3.160)
Latgale				3.304	3.191
				(2.611)	(2.618)
Part-time					3.172
					(4.977)

Note: The table presents OLS equation coefficients. The dependent variable is the percentage amount of the relative wage range; the coefficients represent percentage point change in the wage range in percentages. Regression (1) is specified by using only ISCO job type variables. (2) includes NACE industry classifications, (3) adds company employee count and profit margin regressors. (4) introduces region dummies and (5) adds the part-time variable.
Reference groups: *Job type:* Elementary occupations; *Industry:* Financial and insurance activities; *Size:* Company size <20; *Region:* Rīga; *Part-time:* equals 1 if the position is part-time and 0 if full time.
Standard errors of coefficients are given in parentheses.
***, ** and * mark significance at 1%, 5% and 10% levels.

Appendix K. Logit and Tobit Regression Results With Low vs. Highly Skilled Occupation Variables (Robustness Check).

Regression results

Regressor:	**Logit Regression**	**Tobit Regression**
Agriculture, forestry and fishing	-0.188*** (.048)	-45.026*** (7.639)
Mining and quarrying	0.138*** (.028)	-12.308 (37.964)
Manufacturing	-0.202*** (.031)	-39.172*** (5.282)
Electricity, gas, steam and air conditioning supply	-0.018 (.076)	-32.797** (13.929)
Water supply; sewerage, waste management and remediation activities	-0.185*** (.064)	-47.309** (10.339)
Construction	-0.262*** (.033)	-42.839*** (5.549)
Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.170*** (.031)	-29.837*** (5.293)
Transportation and storage	-0.281*** (.035)	-50.186*** (5.822)
Accommodation and food service activities	-0.227*** (.053)	-37.604*** (8.340)
Information and communication	-0.002 (.031)	7.147 (5.226)
Real estate activities	-0.274*** (.052)	-62.420*** (8.281)
Professional, scientific and technical activities	-0.139*** (.035)	-28.625*** (5.742)
Administrative and support service activities	-0.196*** (.034)	-28.957*** (5.649)
Human health and social work activities	-0.269*** (.038)	-65.085*** (6.312)
Arts, entertainment and recreation	-0.422*** (.131)	-87.395*** (24.356)
Other service activities	-0.160 (.090)	-18.952 (13.799)

Regressor:	**Logit Regression**	**Tobit Regression**
Low skilled occupation	**-0.095*** (.012)**	**-17.230*** (1.855)**
Company size 20-49	0.000 (.016)	1.856 (2.523)
Company size 50-199	-0.024 (.015)	1.210 (2.354)
Company size 200-499	0.017 (.018)	8.137*** (2.632)
Company size 500+	-0.048*** (.018)	-6.697** (2.773)
Profit margin	0.001 (.001)	0.052 (.071)
Pierīga	0.014 (.017)	1.463 (2.711)
Kurzeme	0.161*** (.019)	12.606*** (3.568)
Zemgale	0.094 (.020)	6.806** (3.312)
Vidzeme	0.068*** (.023)	1.611 (3.868)
Latgale	-0.005 (.019)	-3.684 (3.102)
Part-time	-0.034 (.038)	-1.984 (6.058)

Note: The table presents logit marginal effects and tobit regression coefficients with the low vs highly skilled occupation variable. Reference groups: *Low skilled occupation:* Highly skilled occupations; *Industry:* Financial and insurance activities; *Size:* Company size <20; *Region:* Rīga; *Part-time:* equals 1 if the position is part-time and 0 if full time.
Standard errors of coefficients are given in parentheses.
***, ** and * mark significance at 1%, 5% and 10% levels.