Is There a Gender Wage Gap in Online Labor Markets? Evidence from Over 250,000 Projects and 2.5 Million Wage Bill Proposals

Estrella Gomez-Herrera[a] and Frank Müller-Langer[a, b *]

[a] European Commission, Joint Research Centre (JRC), Directorate Growth & Innovation, Digital Economy Unit, Seville, Spain

[b] Max Planck Institute for Innovation and Competition, Munich, Germany

09 July 2019

Abstract

We explore whether there is a gender wage gap in one of the largest EU online labor markets, PeoplePerHour. Our unique dataset consists of 257,111 digitally tradeable tasks of 55,824 hiring employers from 188 countries and 65,010 workers from 173 countries that made more than 2.5 million wage bill proposals in the competition for contracts. Our data allows us to track the complete hiring process from the employers' design of proposed contracts to the competition among workers and the final agreement between employers and successful candidates. Using Heckman and OLS estimation methods we provide empirical evidence for a statistically significant 4% gender wage gap among workers, at the project level. We also find that female workers propose lower wage bills and are more likely to win the competition for contracts. Once we include workers' wage bill proposals in the regressions, the gender wage gap virtually disappears, i.e., it is statistically insignificant and very small in magnitude (0.3%). Our results also suggest that female workers' higher winning probabilities associated with lower wage bill proposals lead to higher expected revenues overall. We provide empirical evidence for heterogeneity of the gender wage gap in some of the job categories, all job difficulty levels and some of the worker countries. Finally, for some subsamples we find a statistically significant but very small "reverse" gender wage gap.

JEL codes: D40; J40

Keywords: Gender wage gap, online labor markets, digitally performable projects

---

[*] The views expressed are purely those of the authors and may not under any circumstances be regarded as stating an official position of the European Commission. We thank Luis Aguiar, Federico Biagi, Nestor Duch-Brown, Joan Calzada, Karin Hoisl, Ulrich Laitenberger, Myriam Mariani, Bertin Martens, Annette Schminke and Joel Waldfogel as well as seminar participants of the Munich Summer Institute 2018, ZEW Conference on the Economics of Communication Technologies, Jornadas de Economía Industrial, CESifo Summer Institute 2019 and JRC Seville Research Seminar for valuable comments and suggestions. The authors also thank Blanca Valdenebro for her valuable help as data assistant. Parts of this paper were written while FML was a visiting researcher at the Max Planck Institute for Innovation and Competition.

I. Introduction

The persistent gender wage gap in traditional labor markets is a fiercely debated issue in economics and policy (Azmat and Ferrer, 2017; Blau and Kahn, 2000, 2013 & 2017; Goldin and Katz, 2016). According to OECD (2018)'s gender wage gap indicator, the average gender wage gap in OECD countries is 14.1%.[1] However, while the gender wage gap and its drivers are well-studied in the context of traditional labor markets, relatively little is known about these questions in the context of online labor markets (OLMs).[2] According to Horton's (2010, p. 516) definition, an OLM is *"a market where (1) labor is exchanged for money, (2) the product of that labor is delivered "over a wire" and (3) the allocation of labor and money is determined by a collection of buyers and sellers operating within a price system."* These OLMs have substantially grown in size and relevance in recent years.[3] For instance, recent evidence from Kässi and Ledhonvirta's (2018) Online Labour Index[4] suggests that the use of online labor has increased by around 20% over the last two years. In addition, Kuek et al. (2015) estimated a total market size of global OLMs of about \$2 billion in 2013, with 48 million registered online workers, and projected a total market size in the range of \$15 billion to \$25 billion in 2020.[5] Finally, as Horton and Prasanna (2015) noted, the high level of detail in OLMs allows the complete hiring process to be tracked. It is in this respect that OLMs provide an ideal framework for studying gender differences in behavior and wages.

In this paper, we explore whether there is a gender wage gap in one of the largest EU OLMs, PeoplePerHour (henceforth, PPH). We also examine to what extent this gap could be attributed to differences in strategic behavior among female and male online workers on the platform. Our analysis provides empirical evidence for a statistically significant 4% gender wage gap among workers. However, we also find that female workers propose lower wage bills and are more likely to win the competition for contracts. Once we include workers' wage bill proposals in the regressions, the gender wage gap, at the project level, virtually disappears, i.e., it is statistically insignificant and very small in magnitude (0.3%).

Our data allows us to track the complete hiring process, which is structured in three phases as illustrated in Figure 1. In the first phase (henceforth, Design), employers describe the contract and post contract proposals for projects. For instance, they choose whether to reveal a budget for a project (Stage 1) and, if so, the amount of the budget (Stage 2). In the second phase (Competition), workers choose whether to propose wage bills for which they are willing to complete a project (Stage 3). Then, if they submit a proposal, workers choose the amount of

---

[1] According to OECD (2018), the gender wage gap is defined as the difference between median earnings of male and female employees and self-employed relative to median earnings of male employees and self-employed.

[2] Notable exceptions are Chan and Wang (2017) and Cook et al. (2018).

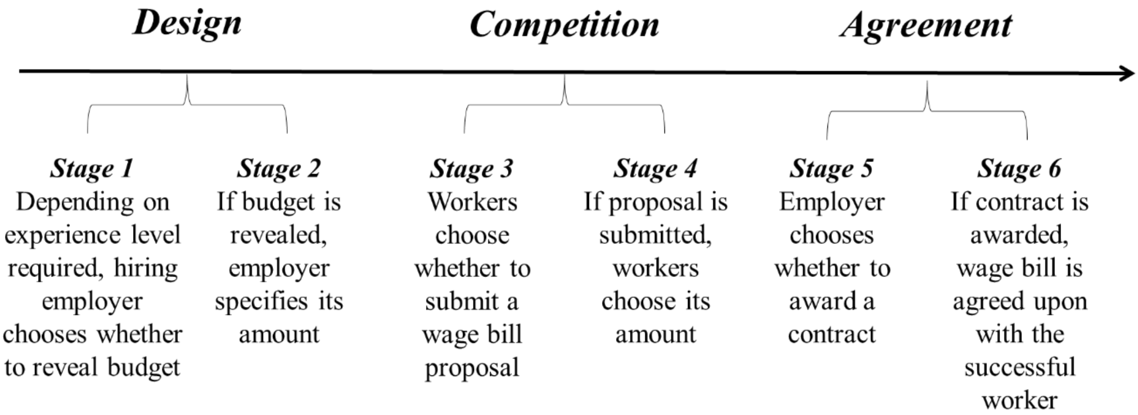
[3] The literature on OLMs dates back to the late 1990s, when, Malone and Laubacher (1998, p. 7) predicted the upsurge of "electronically connected freelancers—e-lancers" that would completely change the labor markets and industrial organization (see also Autor (2001) and Malone and Laubacher (2003)). Two decades later, the body of literature on this topic has grown substantially. For instance, see Horton and Prasanna (2015) and the literature cited therein.

[4] This index provides an OLM equivalent to conventional labor market statistics and shows how the use of online labor changes over time.

[5] See also the references cited in Kuek et al. (2015).

the wage bill (Stage 4). In the third phase (Agreement), employers choose whether to award a contract (Stage 5) and, if so, agree with the workers awarded the contract on the actual wage bills (Stage 6).

Figure 1 | Timing of Competition for Contracts



Our data also allows us to estimate workers' probability of success and expected revenues at the time of proposing a wage bill, i.e., at Stage 3. It is in this respect that we can explore the trade-off between higher wage bill proposals and lower probability of success in terms of expected revenue. Our results suggest that female workers' higher probability of success associated with lower wage bill proposals lead to higher expected revenues.

The main source of our data is PPH, a global OLM platform that delivers purely digital services that require no physical proximity between workers and employers. It was founded in 2007 in London and is one of the largest EU-based OLMs for digital tasks (henceforth, projects). It receives on average around 3 million monthly visits from about 800,000 unique visitors, according to SimilarWeb data.[6] From the platform we obtain information on employer, project and worker characteristics (see Section II).

Our sample consists of 257,111 digitally performable projects posted by 55,824 hiring employers from 188 countries and 65,010 workers from 173 countries that submitted more than 2.5 million wage bill proposals in the competition for contracts. The company data provided by PPH is remarkably comprehensive and detailed.[7] It is in this respect that PPH provides an ideal framework for studying gender differences in behavior and wages. We take advantage of the unique company data to explore the drivers of agreed wages at the project level in more detail than is typically possible for traditional labor markets. In terms of methodological approach, our data allows us to use Heckman correction to mitigate selection concerns. In particular, each of the three phases (see Figure 1) consists of two separate stages. In all three phases, the initial stage is the first stage in a two-stage Heckman model.

[6] We obtained this proprietary data under a subscription from https://www.similarweb.com (last accessed 12 December 2018).

[7] Note, however, that PPH neither collects nor provides information on the gender of employers and workers. We use data from Gender API to obtain the gender variables used in our study (see Section II).

To the best of our knowledge, there is relatively little empirical evidence on gender wage gaps in OLMs. Notable exceptions are Chan and Wang (2017) and Cook et al. (2018). Chan and Wang (2017) explore whether a worker's gender has an effect on the hiring decision of employers on OLMs. However, they do not examine possible gender wage gaps, noting that this aspect deserves further research. Our analysis differs from Chan and Wang (2017) in several important aspects. Chan and Wang (2017) observe hourly wages but do not observe the hours worked. In addition, they do not explore the gender wage gap at the level of wage bills of single projects. The latter aspect is at the core of our analysis. At first glance, our finding that female workers are more likely to win the competition for contracts appears to be in line with Chan and Wang's (2017) finding of a positive hiring bias in favor of female workers. For instance, they find that a female worker's odds of being hired are 13% higher than the odds of a male worker. In line with Chan and Wang (2017), we find that female workers are more likely to be hired. However, we also find that female workers make substantially lower wage bill proposals, which can partly explain female workers' higher probability of being awarded contracts. It is in this respect that our results suggest that the higher winning probabilities of female online workers result from a rational (and not necessarily "biased") selection decision of employers. Our paper is also related to Cook et al. (2018), who analyse whether there is a gender wage gap on Uber. They provide evidence for a 7% gender wage gap on Uber which is caused by differences in experience on the platform, preferences over working time and location, and preferences for driving speed. In contrast to Cook et al. (2018), who consider physically and locally performed driving services, we explore purely digital tasks that have a global reach.

We also put five findings on gender inequalities obtained from prior works in the context of traditional labor markets to the test on OLMs.[8] First, one strand of literature suggests that gender differences in behavior may explain differences in labor market outcomes (Babcock et al., 2017; Buser et al., 2014; Czibor et al., 2018).[9] A sub-strand of this literature suggests that men and women behave differently in wage negotiations (Gerhart and Rynes, 1991; Babcock and Laschever, 2003; Babcock et al. 2017). For instance, Hall and Krueger (2012) use survey evidence from about 1,300 respondents to explore how workers and prospective employers determine agreed wages at the beginning of the job. Their results suggest that the incidence of wage bargaining is lower for women. However, it remains unclear whether behavioral differences between men and women also translate into a gender wage gap in OLMs. Our

[8] Recent empirical evidence suggests that the gender wage gap on traditional labor markets has substantially declined over the past 30 years (Blau and Kahn, 2000 & 2017). However, Blau and Kahn (2017) also suggest that the gender wage gap has declined more slowly at the top of the wage distribution and that the remaining gender wage gap can partly be explained by gender differences in occupations and industries. See also Altonji and Blank (1999) and Bertrand (2011) for a general overview of the literature on gender wage gaps.

[9] In this line, Azmat and Petrolongo (2014) suggest that women appear to gain less from negotiation and have different preferences for competition than men. Reuben et al. (2015) and Niederle and Vesterlund (2007) also provide evidence of gender differences in competitive situations. Dittrich et al. (2014) use evidence from a controlled experiment and show that women obtain worse bargaining outcomes than men when they take on the role of employees. Nelson (2015) provides a survey of the literature on differences in risk-aversion between men and women. See also Charnes and Gneezy (2012). In a survey of the literature, Croson and Gneezy (2009) identify robust gender differences in risk preferences, social preferences and competitive preferences. Their findings suggest that women are more averse to competition than men. See also Dittrich et al. (2014) and Gneezy et al. (2003).

research is a first attempt to fill this gap. In particular, we find that gender differences in behavior, as measured by the size of wage bill proposals, almost entirely explain the gender wage gap that we find at the project level.

Second, recent empirical works typically explore the gender wage gap in a given industry or field and attempt to disentangle potential drivers of the gender wage gap. For instance, Azmat and Ferrer (2017) provide evidence for a large gender gap in workplace performance that explains a considerable share of the gender wage gap among US lawyers. In addition, Bertrand et al. (2010) study possible gender wage gaps among MBA graduates. They provide empirical evidence for a 4% gender wage gap which increases in post-MBA experience. Hoisl and Mariani (2017) explore the gender wage gap in industrial research and find that female inventors earn 14% less than male inventors. They also find that this gender wage gap is not associated with the quality of inventions made by female and male inventors. In contrast to the aforementioned industry-level studies which typically explore the gender wage gap in terms of monthly or yearly earnings, our data allows us to explore the gender wage gap at the level of agreed wage bills for single projects. In particular, we use data from digitally performable projects from 17 different job categories ranging from Design and Creative Arts to Business Support and Web and Software Development (see Appendix 1).

Third, as for the drivers of the gender wage gap, Blau and Kahn (2013) suggest that women typically have less labor market experience and on-the-job learning and training. Therefore, they argue that it is important to add measures of actual workers' experience for analyzing gender wage gaps.[10] As suggested by Blau and Kahn (2013), we include a measure for in-platform worker experience in our analysis. We find that female workers have substantially less in-platform work experience than male workers.

Finally, an important difference of OLMs as compared to traditional markets is how trust is created – this being one of the main workers' characteristics that generate value added. While traditional markets rely on repeated personal interaction to create trust (Cabral and Hortaçsu, 2010), online markets without physical interactions require other mechanisms such as review scores.[11] In this regard, we explore the impact of workers' rating scores on the competition for contracts and the hiring decision. Our results provide evidence for a statistically significant, positive marginal effect of workers' rating scores on their agreed wage bills.

[10] However, Bayard et al. (2003) find that selection of women into lower-paying jobs accounts for a substantial fraction of the gender wage gap in the US. Recent empirical evidence from Portugal suggests that firm-specific pay premiums are an important source of the gender wage gap (Card et al., 2016). In particular, Card et al. (2016) find that female employees receive about 90% of the pay premiums that male employees earn. Finally, Goldin (2014) suggests that the gender wage gap may be reduced if temporal flexibility were enhanced. It is in this respect that OLMs are often seen as a potential means to generate more temporal job flexibility that may eventually favor female employees (Cook et al., 2018).

[11] See Pallais (2014), who demonstrates the crucial importance of a first job reference in order for workers to get started in an OLM. In addition, Straub et al. (2015) use Amazon Mechanical Turk to test the efficiency of rank-order tournaments versus piece rates in term of incentives for crowd workers. Their results show the effects of feedback on worker's performance.

The remainder of the paper is organized as follows. In Section II, we present the data and describe the variables under study. Section III addresses our methodological approach. In Section IV, we present and discuss our results. Section V concludes.

II. Data and Variables

Our dataset contains information on employer, project and worker characteristics and covers all transactions on PPH from Nov 2014 to Oct 2016. It comprises 257,111 posted projects from 17 different categories such as Web Development, Design or Software Development (see Appendix 1) involving 55,824 employers from 188 countries and 65,010 workers from 173 countries. These projects received 2,665,361 wage bill proposals in total. Out of the 257,111 posted projects, 134,913 were eventually awarded. These awarded projects received, in total, 1,255,778 wage bill proposals. The remaining wage bill proposals were tendered for projects that were eventually not awarded. For the 134,913 awarded projects, the payment is agreed on the basis of the winning wage bill proposal.[12] The total wage bill for these projects reached nearly 20 M€, with an average of 183€ per project. We decompose wage bill projects into price (wage) and quantity (time). We assume that the wage bill that a worker indicates in her[13] wage bill proposal is given by the number of hours to complete the project multiplied by the expected hourly wage. Then, we obtain the approximate number of hours to complete a project by dividing the average proposed wage bill of all workers that submitted a proposal by the average expected wage of all workers that submitted a proposal.[14]

To obtain the gender variables, we use data from Gender API.[15] Both employers and workers provide a name when they register on the platform. We use those names, along with the country where employers and workers are located, to retrieve the gender in Gender API. In total, we obtained positive responses for 97% of the employers' names and 90% of the workers' names. Negative responses relate to cases where a given name cannot be assigned to any gender because it is a pseudonym, corresponds to a firm's name or is not stored in the gender dataset. Taking a random sample of 400 names we calculate the probability of error in the gender assignment. We compare the gender obtained from the workers' pictures with the respective results from the name-based gender assignment. Results show that for 92.5% of the cases the gender is correctly assigned. In 4% of the cases the gender is not identifiable (because there is no picture and the names are gender neutral) and in 3.5% of the cases the algorithm attributed an incorrect gender. We address this concern by running the regressions

---

[12] Wage bills are the product of wage and working time (price multiplied by quantity).
[13] Throughout the manuscript, we use the terms she/he (her/his) interchangeably.
[14] In the phase where employers design and post a project (Design) and in the phase where workers make their wage bill proposals (Competition), we use the *approximate* number of hours required to complete a project as proxy for project size. In the subsequent phase where employers and workers agree on a wage bill (Agreement), we use the *actual* wage bill proposal as proxy for project size.
[15] See https://gender-api.com/ (last accessed 21 January 2019).

using a restricted sample where the accuracy of the gender assignment is above 95%.[16] Results remain qualitatively unchanged.

A. Design

Table 1 provides an overview of the variables used in the design phase, aggregated at the project level. Overall, it shows that male employers post around two-thirds of the projects (67.2%) whereas female employers post less than one-third (24.4%).[17]

[Table 1 HERE]

For this phase, we have two different dependent variables. For the first stage, we create a binary variable, *BudgetProposed*, which equals 1 if the employer proposes the budget for a specific project and 0 otherwise. In the second stage, the dependent variable is the specific amount of the budget proposed, *Budget*, if it is revealed. As we observe in Table 1, female employers post, on average, substantially lower budgets than male employers (€77.12 vs. €119.5).

Our main variable of interest, *EmployerFemale*, takes value 1 if the employer is female and 0 otherwise. We control for projects where the employer gender is not known and for other employer characteristics such as experience on the platform. Male employers have, on average, more experience than female employers (6.3 vs. 5.7 posted projects). From the past behavior of the employer, we construct the exclusion variable: the share of projects posted in the past in which the employer has revealed the budget. We expect this variable to affect the decision of revealing or not (Stage 1) but not the amount of the revealed budget (Stage 2). Finally, we include a set of controls to capture other project characteristics such as the experience level and the number of hours required to complete a project. For instance, Table 1 shows that the projects posted by male employers are typically larger than those posted by female employers (13.9 vs. 9.6 hours).

B. Competition

Table 2 reports the descriptive statistics for variables in the competition phase, at the level of wage bill proposals. Similarly to the share of male to female employers, the number of proposals made by male workers is almost triple that of proposals by female workers (61% vs. 20%).[18]

[Table 2 HERE]

For this phase, we have two different dependent variables. First, *ProposalDummy* indicates whether a worker makes a wage bill proposal for a given project. We observe when a wage bill proposal is tendered for a given project. However, we do not observe the projects that a worker considered to be interesting but to which he eventually did not submit a wage bill

---

[16] Along with the result of each query, Gender API provides a value ranging between 0 and 100 that determines the reliability of the outcome.

[17] In 8.4% of the projects the gender of the employer is not known.

[18] In 19% of the wage bill proposals the gender of the worker is not known.

proposal. We can deduce this specific worker behavior from other choices he makes. More specifically, our data allows us to define a set of projects which are "similar" to the project for which a proposal was actually made. Hence, we assume that a given worker has seen all similar projects before making a proposal. We define projects as similar if they have been posted on the same day, are in the same job category and require the same experience level. Notably, these three criteria correspond to the filters that PPH provides workers with to pre-select a set of potentially interesting projects. Doing this, we obtain that a worker browses through, on average, 20 projects before he makes a decision to propose a wage bill. This assumption is equivalent to restricting the average search of a worker to the first screen he sees after applying the aforementioned filters. That is, we argue that a worker browses the first selection of 20 projects but does not click through the second screen.

The second dependent variable, *ProposalAmount* indicates the amount of the wage bill proposal of a worker, conditional on a proposal being made. Table 2 shows that, on average, female workers make lower wage bill proposals (€328.8 vs. €475.8).

The main variables of interest relate to gender. The gender of the worker is given by *WorkerFemale*, which takes value 1 when the worker is female. In 19% of cases, we were not able to identify the gender. We control for this by including a binary variable that takes value 1 when a worker’s gender is not identifiable.

We include three control variables for workers. First, we include their in-platform experience as measured by the cumulative number of prior projects that each worker has completed. On average, female workers have substantially less experience on the platform (342.5 vs. 527.4 projects completed). Second, we include the average certificate that the platform assigns to the worker on the basis of the bill generated and other behavioral aspects.[19] It ranges from 1 to 6 and, as we observe in Table 2, it is almost identical for male and female workers (4.281 vs. 4.218). Finally, we include a dummy variable that takes value 1 when at least one of the skills specified by the worker in her profile matches the skills required for the completion of the project. This variable is also very similar for both genders. We control for employer gender and the cases where employer gender is unknown.

As controls for project characteristics, we include the number of words in the description, a dummy that indicates whether there are files attached or not, a dummy indicating whether the budget is revealed, variables for the experience required for the project and the number of hours required as a proxy for the size of the project. On average, female workers make proposals for smaller projects than male workers (12.6 vs. 18.3 hours). As an exclusion variable, we use the average number of wage bill proposals made by a given worker in a given day. We expect this variable to affect the worker's decision of whether or not to make a wage bill proposal (Stage 3) but not the amount of the proposed wage bill (Stage 4).

[19] This certificate provides a measure for the quality of the workers. It is based on the quantity of work billed by the worker through the platform and other aspects on general behavior, for instance, responding fast to messages, delivering on time and avoiding things like disputes, cancellation/abandoning of work and refunds. See https://support.peopleperhour.com/hc/en-us/articles/205218587-What-is-CERT- for further information on this measure (last accessed 12 December 2018).

C. Agreement

Table 3 provides an overview of the variables used in the agreement phase, at the level of wage bill proposals.

[Table 3 HERE]

Again, we have two dependent variables. First, for each wage bill proposal that the employer receives, he decides whether or not to award it with a contract. We capture this with the dummy variable *ProposalAccepted*. Second, conditional on accepting, he agrees with the winning worker on the amount that he will spend on that project, *AgreedWageBill*. From Table 3 we can see that, on average, female workers make substantially lower wage bill proposals (€328.8 vs. €475.8) and have a substantially higher probability of winning the contract (7.1% vs. 4.7%). Finally, female workers obtain substantially lower agreed wage bills (€141.7 vs. €193).

Our main variable of interest is the gender of the worker, *WorkerFemale*. We control for unknown gender and for other worker characteristics such as experience, certificate and skills match with the project requirements. Additionally, we include the number of words in workers' profiles as a proxy for the evaluation costs that each wage bill proposal generates for the employer (e.g., reading costs).

As project controls we include a dummy indicating whether the budget is revealed and a continuous variable indicating the number of wage bill proposals made by competing workers. As for the experience level required, we can see from Table 3 that 62.4% of all wage bill proposals are made for projects that require an intermediate level of experience (expert level: 23.4%). In addition, we control for employer gender and employer experience. As an exclusion variable, we use the cumulative number of projects awarded by a given employer in a given category.

Figure 2 illustrates the mean agreed wage bill by experience level required. It suggests that the agreed wage bill increases in the experience level required for a project.[20]

[20] Appendix 2 provides histograms for the distribution of size, amount of wage bill proposals, agreed wage bills and budgets per project.

Figure 2 | Mean Agreed Wage Bills by Gender of Workers

Notes: Figure 2 illustrates the mean agreed wage bills by worker gender, overall (as given by the three columns on the left-hand side), and by the three possible experience levels required. The experience level required for a job (Entry, Intermediate or Expert) is determined by the employers. *N* indicates the number of proposals accepted overall and for each experience level separately.

III. Empirical Design

We use a Heckman model to estimate the three subsequent phases of two-stage decisions. Heckman (1979) notes that using non-randomly selected samples to estimate behavioral relationships may lead to biased results because of a missing data problem. In our empirical framework, measuring the determinants of the second stage in each phase without taking into account the respective first stage could bias the estimation. In the first step, a Probit equation defines the outcome of a binary decision problem. In the second step, we use OLS to estimate the expected values of the outcome variable conditional on the first decision. A selection variable is required in order to identify the parameters in both equations. This selection variable should only affect the decision process and should be uncorrelated with the respective second stage. We define a selection variable for each of the three phases.[21] The Heckman model can be estimated by using either Heckman's two-step consistent estimator or full maximum likelihood. In our analysis we use the two-step estimator since it allows for robust standard errors and clustering. In the regressions we use the log transformed versions of the continuous variables under study.

For the design phase, the selection equation (Stage 1) is given by:

[21] See Section II.

$$BudgetProposed_{ip} = \beta_0 + \beta_1 EmployerFemale_i + \beta_2 X_i + \beta_3 X_p + \beta_4 ShareProjectsBudgetProposed_{icat} + \mu_d + \mu_{ci} + \mu_{cat} + \varepsilon_{ip} \quad (1)$$

and the regression equation (Stage 2) is:

$$LogBudget_{ip} = \beta_0 + \beta_1 EmployerFemale_i + \beta_2 X_i + \beta_3 X_p + \mu_d + \mu_{ci} + \mu_{cat} + \rho_{ip} + \varepsilon_{ip}. \quad (2)$$

Subscript *i* denotes the employers (*j*: workers; *p*: projects). X_i and X_p are vectors of controls for employer and project characteristics, respectively.[22] Day dummy variables are given by μ_d. Dummy variables for the countries where the employers are located are given by μ_{ci} (μ_{cj}: dummy variables for countries of workers). The dummy variables for the 17 project categories are given by μ_{cat}. The exclusion variable is $ShareProjectsBudgetProposed_{icat}$. It indicates the share of projects posted in the past where the employer has revealed the budget in the same category as the project posted. Finally, ε_{ip} is the error term and ρ_{ip} is the mills ratio.

For the competition phase, we first estimate the following equation (Stage 3):

$$ProposalDummy_{ijp} = \beta_0 + \beta_1 WorkerFemale_j + \beta_2 X_j + \beta_3 X_i + \beta_4 X_p + \beta_5 AverageNumberProposals_{jd} + \mu_d + \mu_{ci} + \mu_{cj} + \mu_{cat} + \varepsilon_{ijp}. \quad (3)$$

X_j, X_i, and X_p are vectors of controls for worker, employer and project characteristics, respectively.[23] The exclusion variable is $AverageNumberProposals_{jd}$. It indicates the average number of proposals made by a given worker in a given day.

In addition, we estimate the following equation using OLS (Stage 4):

$$LogProposalAmount_{ijp} = \beta_0 + \beta_1 WorkerFemale_j + \beta_2 X_j + \beta_3 X_i + \beta_4 X_p + \mu_d + \mu_{ci} + \mu_{cj} + \mu_{cat} + \rho_{ijp} + \varepsilon_{ijp}. \quad (4)$$

For the selection equation in the agreement phase (Stage 5) we specify the following model:

$$ProposalAccepted_{ijp} = \beta_0 + \beta_1 WorkerFemale_j + \beta_2 X_j + \beta_3 X_i + \beta_4 X_p + \beta_5 ProjectsAwarded_{icat} + \mu_d + \mu_{ci} + \mu_{cj} + \mu_{cat} + \varepsilon_{ijp}. \quad (5)$$

X_j, X_i, and X_p are vectors of controls for worker, employer and project characteristics, respectively.[24] The exclusion variable is $ProjectsAwarded_{icat}$. It indicates the cumulative number of projects awarded by a given employer in a given category.

Finally, the regression equation determining the agreed wage bill (Stage 6) is given by:

[22] The list of variables included in the vectors of controls is provided in Section II.A (see also Table 1).
[23] The list of variables included in the vectors of controls is provided in Section II.B (see also Table 2).
[24] The list of variables included in the vectors of controls is provided in Section II.C (see also Table 3).

$$LogAgreedWageBill_{ijp} = \beta_0 + \beta_1 WorkerFemale_j + \beta_2 X_j + \beta_3 X_i + \beta_4 X_p + \mu_d + \mu_{ci} + \mu_{cj} + \mu_{cat} + \rho_{ijp} + \varepsilon_{ijp}. \quad (6)$$

There is a potential caveat in the estimation of the model due to the existence of a limit in the inclusion of variables. For linear models, the estimation of fixed effects simply represents the average value of the dependent variable for a given individual after controlling for covariates. Estimating a fixed effects model for non-linear regressions, however, has different implications. Neyman and Scott (1948) note the problem of incidental parameters, i.e., in the presence of these parameters the maximum likelihood estimation of the structural parameters may not be consistent. As they remark, this failure occurs because the dimension of incidental parameters increases with the sample size, affecting the ability of maximum likelihood estimation to consistently estimate the structural parameters.[25] However, as pointed out by Lee and Phillips (2015) and Greene (2004), there is a trade-off between capturing the unobserved heterogeneity via the fixed effects and avoiding the bias derived from the incidental parameters problem. Besides this, the incidental parameter problem is nuanced when the sample is large. Note that our sample consists of more than one million observations. Based on these arguments, we choose to estimate the Heckman model including a set of dummy variables to control for employer and worker country, day and category fixed effects, as defined in Section III.

Ideally, in the Probit regressions, we would also be able to control for all the unobserved heterogeneity derived from characteristics related to each specific employer and worker by including a set of employer and worker dummies. However, given the large number of variables that this implies, the estimation of Heckman would lead to inconsistent estimates. For this reason, in Tables 4, 5 and 6, we include additional columns with OLS regressions including employer and worker fixed effects alternatively using the *areg* command in Stata.

IV. Gender Differences in Behavior and Wages

We subsequently present our results following the three phases (Design, Competition and Agreement) as illustrated in Figure 1. Then, we present the results from the analysis of different subsamples. Finally, we explore gender differences in expected revenue.

A. Design

Table 4 reports the coefficients obtained from our regressions for the Design phase, i.e., Stages 1 and 2. We run the regressions with four different specifications. Specification (1) reports results for Stage 1.[26] Specifications (2) to (4) report the results for Stage 2. In all

[25] Even if we use the two-step estimator instead of the maximum likelihood procedure, there could be a bias associated with the Probit estimation in the first stage.
[26] As noted by Cameron and Trivedi (2010), we cannot directly interpret the magnitude of an effect from the coefficients from a nonlinear regression; only the sign and significance. We therefore show in Appendix 3 the marginal effects at the means (MEMs) after Probit regressions for Stage 1, Stage 3 and Stage 5, respectively.

specifications, we include the variables relating to employer and project characteristics as reported in Table 1. In column (1), we include the exclusion variable, i.e., the share of projects on the same day and in the same category where budget is revealed. In columns (1), (2) and (3), we include dummy variables for days, categories and employer countries. Column (3) is the basis for column (4), where we include employer dummies instead of employer country dummies.

[Table 4 HERE]

We obtain the following main results. First, female employers are less likely to reveal the budget for a project. The coefficient for *EmployerFemale* is negative and statistically significant. Second, where they reveal the budget, female employers post lower budgets. As for the in-platform experience of employers, we find that more experienced employers are more likely to reveal the budget and post lower budgets. Finally, our results suggest that larger and more difficult projects have higher budgets.

B. Competition

Table 5 reports the coefficients obtained from our regressions for the competition phase, i.e., Stages 3 and 4. We run the regressions with seven different specifications. Specification (1) reports results for Stage 3. Specifications (2) to (7) report results for Stage 4. In all specifications, we include (where possible) the variables relating to worker, employer and project characteristics as reported in Table 2. We also include dummy variables for days and categories. In column (1), we include the exclusion variable, i.e., the average number of wage bill proposals made by a worker in a given day. Column (2) is the basis for column (3). In columns (1), (2) and (3), we include dummy variables for employer and worker countries. In column (4), we include worker dummies instead of worker country dummies whereas in column (5) we include employer dummies instead of employer country dummies. Column (5) is the basis for column (6), where we include an interaction term between *WorkerFemale* and *BudgetProposed* to explore whether female workers react differently to proposed budgets. Finally, we include project dummies instead of employer and worker dummies in column (7).

[Table 5 HERE]

We find that female workers are more likely to submit a wage bill proposal. The coefficient is positive and statistically significant at the 1% level. As the results reported in Appendix 3 show, the probability of tendering a wage bill proposal increases by 0.1 percentage points if the worker is female.[27]

The MEMs show how P(Y=1) changes as the independent variables change from 0 to 1 (if categorical), or in one unit (if continuous), using the mean values for the rest of variables in the regression (Williams, 2012).

[27] Note that, due to computational limitations, we can only calculate the MEMs for a random 10% of the sample. Furthermore, Appendix 4 (A) shows the marginal effects at representative values of project size (number of hours) for *WorkerFemale* =1 on the probability of making a wage bill proposal. It suggests that the marginal effect is positive and small in magnitude, i.e., it does not exceed 0.21 percentage points. It slightly increases in project size. Similarly, Appendix 4 (B) shows that the marginal effects at representative values of project size (number of hours) for *BudgetProposed*=1 on the probability of submitting a wage bill proposal. It suggests that

Notably, we find that female workers, conditional on submitting a wage bill proposal, make lower wage bill proposals. As reported in Table 5, the marginal effect for *WorkerFemale* ranges from about -8 percentage points in column (2) to about -4 percentage points in (7). In addition, conditional on making a wage bill proposal, workers make substantially lower wage bill proposals when the budget is revealed. As given by Table 5, the marginal effect of *BudgetProposed* ranges from about -38 percentage points in column (4) to -62 percentage points in column (2). More experienced workers and workers whose skills match the required skills make higher wage bill proposals. Finally, the coefficient for the interaction term between *WorkerFemale* and *BudgetProposed* is statistically significant at the 1% level and positive. This suggests that female workers react differently to revealed budgets when they specify the amount of their wage bill proposals.

C. Agreement

Table 6 reports the coefficients obtained from our regressions for the agreement phase, i.e., Stages 5 and 6. We run the regressions with five different specifications. Specification (1) reports results for Stage 5. Specifications (2) to (5) report results for Stage 6. In all specifications, we include (where possible) the variables relating to worker, employer and project characteristics as reported in Table 3. We also include dummy variables for days. In column (1), we include the exclusion variable, i.e., the (log-transformed) cumulative number of projects awarded by an employer in a given category. In columns (1) and (2), we include dummy variables for categories, employer countries and worker countries using the Heckman estimation method. In column (3), we include employer dummies instead of employer country dummies. Due to the incidental parameters problem discussed in Section III, we use OLS to test the robustness of our results. In subsequent columns, we modify the specification to explore the potential drivers of a possible gender wage gap. Hence, column (4) replicates column (3) excluding the amount of the wage bill proposals. In column (5), we include the amount of the wage bill proposals but refrain from including category dummies, worker country dummies and employer dummies. The purpose of columns (4) and (5) is to explore whether the omission of the amount of the wage bill proposals and/or the omission of the aforementioned binary variables has a substantial effect on our results.

[Table 6 HERE]

Our main results are as follows. First, we provide evidence for a statistically significant gender wage gap in columns (4) and (5), where we use "inferior" methods. The marginal effect of *WorkerFemale* ranges from -4.1 percentage points in column (5) to -1.4 percentage points in column (4). In contrast, the gender wage gap virtually disappears when we include the amount of the wage bill proposals and the dummies for categories and worker countries in the regressions reported in columns (2) and (3). The gender wage gap is not statistically significant (at the 5% level) and small in magnitude, ranging from -0.3 percentage points in column (3) to -0.5 percentage points in column (2). Seeing as R-squared increases from 0.605

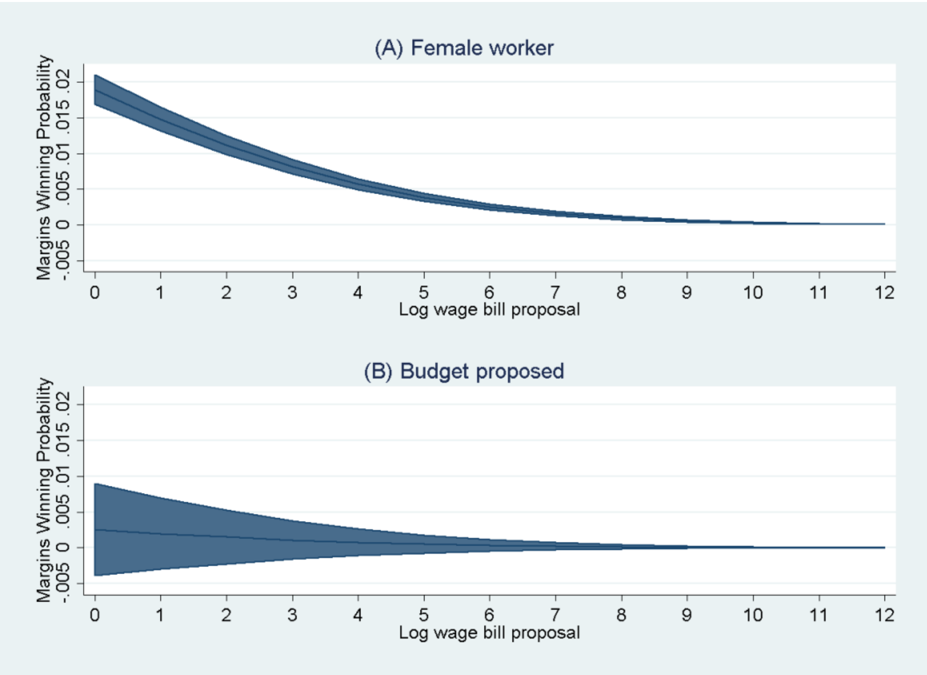
---

the marginal effect of *BudgetProposed*=1 never exceeds 0.3 percentage points and is slightly increasing in project size.

in column (2) to 0.831 in column (3), where we include the employer dummies, we consider column (3) as our preferred specification.

However, in line with Chan and Wang (2017), we also find that female workers are more likely to be awarded contracts. As reported in column (1), the coefficient of *WorkerFemale* is positive and statistically significant at the 1% level.[28] More specifically, Appendix 3 shows that the probability of a proposal being accepted increases in 0.4 percentage points when the worker is female.

Figure 3 | Marginal Effects of (A) Female Workers and (B) Budget Proposed on the Probability of Success, by Project Size



Notes: Figure 3 shows the marginal effects at representative values of project size (wage bill) for (A) *WorkerFemale=1* and (B) *BudgetProposed=1* on the probability of winning the competition for contracts (Stage 5). The horizontal axis indicates project size as given by the log wage bill proposal. The vertical axis indicates the marginal effects on the probability of winning the competition. We indicate 95% confidence intervals. We use the *marginsplot* command in Stata to create this figure. We obtained this figure using the full sample of 2,664,701 observations used to obtain the regression results reported in column (1) of Table 6. Figure 3 (A) shows that the marginal effect at the means of *WorkerFemale=1* on the probability of winning the contract is positive and about +2 percentage points for small projects. It decreases in project size and tends towards zero for very large projects. Figure 3 (B) shows that the marginal effect at the means of *BudgetProposed=1* is not statistically significant and is negligibly small in magnitude.

Figure 3 (A) shows that the marginal effect at the means of *WorkerFemale* on the probability to win the contract is positive and about +2 percentage points for small projects. It decreases

[28] We also ran Stage-5 regressions excluding the amount of the wage bill proposal (results not reported). The coefficient of *WorkerFemale* increases from 0.098 to 0.108 when we refrain from including the amount of the wage bill proposals in the regressions.

in project size and tends towards zero for very large projects. Figure 3 (B) shows that the marginal effect at the means of *BudgetProposed* is not statistically significant and negligibly small in magnitude.[29] In addition, our results suggest that more experienced employers obtain lower agreed wage bills. Finally, we provide empirical evidence that agreed wage bills are higher for (a) larger projects, (b) more difficult projects, and (c) workers with a better fit in terms of required skills.[30]

We make two final remarks. First, the positive sign of *BudgetProposed* in column (2) of Table 6 is somewhat counterintuitive for the following reason. From Stage 4, where workers compete in terms of wage bill proposals, we know that revealing the budget leads to lower wage bill proposals (see columns (2) to (6) of Table 5). Therefore, we would expect also to obtain lower agreed wage bills when the budget is revealed in the agreement phase as reported in Table 6. We can solve this puzzle as follows. When we exclude the amount of the wage bill proposal in column (4) of Table 6, we find that the effect of *BudgetProposed* is negative and statistically significant at the 5% level. This suggests that the amount of the wage bill proposal is actually picking up this effect. When the amount of the wage bill proposal is not included, the sign of *BudgetProposed* is negative – as expected.

Second, there may be some concerns that female workers self-select into larger projects which in turn may countervail a possible gender wage gap. We address this concern graphically. Appendix 4 (A) shows that the marginal effect (at representative values of project size) of a discrete change in the female worker dummy on the probability of making a wage bill proposal is positive but very small in magnitude, i.e., it does not exceed 0.21 percentage points for different levels of projects size. However, Appendix 4 (A) also suggests that the marginal effect of *WorkerFemale* slightly increases in project size. This result points to some degree of selection of female workers into larger projects. However, this effect is very small. In addition, we mitigate these selection concerns by controlling for project size, i.e., we include the amount of wage bill proposals in the regressions reported in columns (1) to (3) of Table 6.

D. Additional Findings

In the following, we explore whether a possible gender wage gap may be sensitive to the job category (Subsection D.1), experience level required for a project (D.2), or country of origin of the worker (D.3). Then, we explore gender differences in expected revenue (Subsection D.4).

1. Gender Wage Gap by Job Category

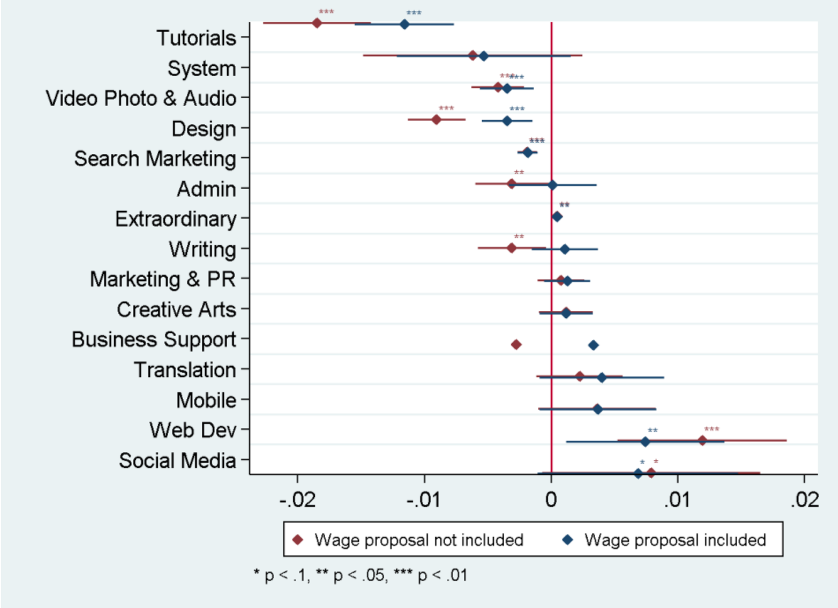
We run the regressions from specifications in Table 6 first excluding the amount of the wage bill proposals (column 4) and then including this amount (column 3) separately for the subsample of projects posted by job category. Results are reported in Figure 4.

---

[29] Figure 3 illustrates the marginal effects at representative values of project size. In Appendix 3, we additionally report the marginal effects at the means for the entire sample.

[30] We also ran the regressions including worker dummies instead of employer dummies. Results remain qualitatively unchanged (results not reported).

Figure 4 | Gender wage gap by job category



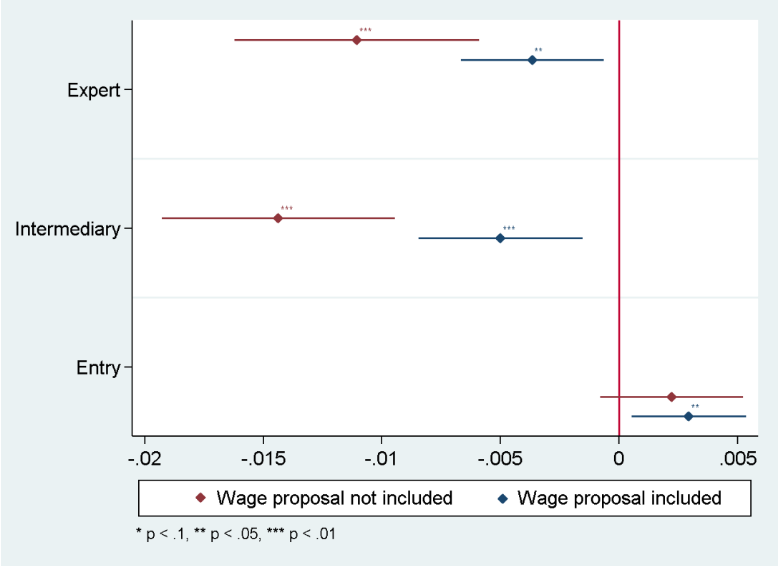
Notes: Figure 4 plots the coefficients of the female-worker dummy from the estimation of specification (3), in blue, and (4), in red, from Table 6 for separate subsamples by job category. Confidence intervals and statistical significance included.

Figure 4 provides additional empirical evidence that the gender wage gap is smaller in magnitude once we include the amount of the wage bill proposals for almost all job categories, with the exceptions of Marketing & PR and Translation. Figure 4 also provides evidence for heterogeneity of the gender wage gap across job categories. For instance, there is a statistically significant gender wage gap (at least at the 5% significance level) in the categories Tutorials (-1.2%), Video, Photo and Audio (-0.3%), Design (-0.3%) and Search Marketing (-0.2%). Notably, we also find evidence for a robust "reverse" gender wage gap for Web Development (+0.7%). However, while we find a statistically significant gender wage effect in these five job categories, it is very small in magnitude ranging from -1.2% to +0.7%. Note that for all other job categories under study the gender wage gap is not statistically significant and smaller than 0.7% in magnitude.

2. Gender Wage Gap by Experience Level Required

We run the regressions from specifications (3) and (4) of Table 6 separately for the three levels of difficulty in which jobs are classified in the platform, according to the experience level required (Entry, Intermediary and Expert). Figure 5 provides empirical evidence for heterogeneity of the gender wage gap across job difficulty levels (see also Figure 2). The gender wage gap is statistically significant for expert-level projects (-0.4%) and intermediary-level projects (-0.5%). There is a statistically significant "reverse" gender wage gap for entry-level projects (+0.3%).

Figure 5 | Gender wage gap by experience level required



Notes: Figure 5 plots the coefficients of the female-worker dummy from the estimation of specification (3), in blue, and (4), in red, from Table 6 for separate subsamples by the three possible experience levels required for a job in the platform (Entry, Intermediate or Expert). Confidence intervals and statistical significance included.

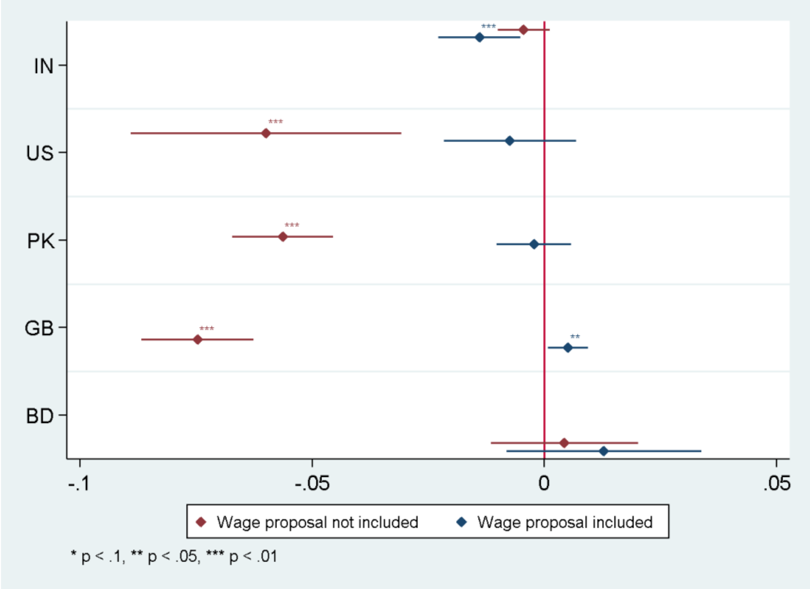
3. Gender Wage Gap by Worker Country

We run the regressions from specification (3) and (4) of Table 6 separately for the top-5 worker countries in the sample[31]. Results are reported in Figure 6.

Results suggest that there is some heterogeneity of the gender wage gap across worker countries. The gender wage gap is statistically significant for workers located in India (-1.4%). Interestingly, this gap cannot be explained by the lower amount of wage bill proposals of female workers as the gender wage gap is not statistically significant and smaller in magnitude when the amount of the wage bill proposals is excluded. We also find that there is a statistically significant "reverse" gender wage gap for workers located in Great Britain (+0.5%). Hence, while we find statistically significant gender wage effects, they are small in magnitude ranging from -1.4% to +0.5%. Note that for the three other top-5 worker countries the gender wage gap is not statistically significant and smaller than 1% in magnitude.

[31] Top-5 worker countries accounts for 92.6% of the total projects finished in the platform.

Figure 6 | Gender wage gap by worker country (Top-5)



Notes: Figure 6 plots the coefficients of the female-worker dummy from the estimation of specification (3), in blue, and (4), in red, from Table 6 for separate subsamples by the top-5 worker countries in the sample (India, US, Pakistan, Great Britain and Bangladesh). Confidence intervals and statistical significance included.

4. Expected Returns

As discussed in the introduction, the literature on gender differences suggests that women tend to propose (and accept) lower wages than men in wage negotiations in traditional (offline) labor markets (see, for instance, Gerhart and Rynes (1991), Babcock and Laschever (2003), Babcock et al. (2017) and Hall and Krueger (2012)). Our results suggest that online workers face a trade-off between the magnitude of the wage bill proposal and the probability to win the competition for contracts. For instance, the higher the initial wage bill proposal the lower is ceteris paribus the probability of being awarded a contract. In addition, our results suggest that female workers tend to solve this trade-off in a different fashion than male workers.

To further explore this gender differential and examine which strategy yields higher expected revenues, we estimate the following empirical proposal-winning function at the project level for a given worker:

$$\hat{p}_{jp} = prob(LogProposalAmount_{jp}, X_j, X_p, WorkerFemale_j) \qquad (7)$$

where $\hat{p}_{jp}$ is the probability of winning the competition for contracts. As before, $LogProposalAmount_{jp}$ is the log-transformed amount of the proposed wage bill. X_j and X_p are worker and project characteristics, respectively. $WorkerFemale_j$ is a binary variable for female workers.

Figure 7 | Wage Bill Proposals, Winning Probabilities and Expected Revenues, by Gender

Notes: The three columns on the left-hand side of Figure 4 illustrate the mean wage bill proposals (in €) for all workers and by worker gender, respectively. The three columns in the middle represent the probability of winning the competition for contracts obtained from the empirical proposal-winning function given by equation (7). Finally, the three columns on the right-hand side of Figure 4 show the expected revenues (in €) obtained from equation (8).

Then, the expected revenue, *ER*, from submitting a wage bill proposal is given by:

$$ER_{jp} = ProposalAmount_{jp} * \hat{p}_{jp} \quad (8)$$

Figure 7 summarizes the results from this exercise. It suggests that the strategy of making lower wage bill proposals and being more likely to win the competition for contracts leads to higher expected revenues. In this respect, our results suggest that female workers, in terms of expected revenues, adopt a more successful strategy than their male competitors.

V. Conclusion

We answer the question raised in the title of the paper as follows. We find that there is a statistically significant gender wage gap of about four percentage points in the OLM under study. However, we also find that female workers propose lower wage bills and are more likely to win the competition for contracts. Once we include workers' wage bill proposals in the regressions, the gender wage gap virtually disappears, i.e., it is statistically insignificant and very low in magnitude (0.3 percentage points). Our analysis is among the first empirical efforts to explore the question of whether there is a gender wage gap in OLMs. Our data allows us to track the complete hiring process, including workers' behavior in the competition for contracts. Based on our results, we argue that a large part of the gender wage gap can be explained by female workers' behavior when they make their wage bill proposals. We find that female workers make lower wage bill proposals. We also find that female workers have a higher probability of winning the competition for contracts. Overall, our results suggest that this behavior allows female online workers to obtain higher expected revenues than their male competitors. Our results also provide empirical evidence for heterogeneity of the gender wage gap in some of the job categories, all job difficulty levels and some of the worker countries.

We should also note some caveats in this empirical exercise. First, there are non-observable steps in the decision process. More specifically, we do not directly observe the workers' decision *not* to make wage bill proposals to some projects. However, our data allows us to infer this decision on the basis of other variables and on how the platform provides a pre-selection of possibly interesting projects based on observed criteria. Additionally, we only observe decisions that workers make on the platform. More information about their outside activities and behavior would be necessary to obtain a complete picture on whether online work is a substitute or complement for traditional "offline" work.

In terms of potential benefits of OLMs for employers, our results suggest that employers may reduce wage cost by imitating the strategy of experienced employers. In particular, we provide evidence that more experienced employers (a) are more likely to reveal the budget, (b) post lower budgets, (c) are less likely to award a contract, and eventually obtain lower agreed wage bills. We argue that by posting the budget employers affect workers' behavior: workers make substantially lower wage bill proposals if the budget is revealed. It is in this respect that revealed budgets may serve as a focal point when workers compete in terms of wage bill proposals.

Overall, our results reveal the importance of gender differences in strategic behavior and winning probabilities for the analysis of gender differences in earnings in OLMs. In traditional (offline) labor markets, these aspects are often not observable at the project level. We show that a possible gender wage gap in OLMs can – to a large extent – be explained by gender differences in behavior. One potential implication of our results is that OLMs may further reduce wage inequalities between male and female workers if these markets continue to grow.

References

Altonji, J. G. and R. M. Blank (1999). Race and Gender in the Labor Market, In: Ashenfelter, O. and D. Card (Eds.). Handbook of Labor Economics, Volume 3, New York: North-Holland.

Autor, D. H. (2001). Wiring the Labor Market. Journal of Economic Perspectives, 15(1), 25–40.

Azmat, G. and R. Ferrer (2017). Gender Gaps in Performance: Evidence from Young Lawyers. Journal of Political Economy, 125(5), 1306–1355.

Azmat, G. and B. Petrolongo (2014). Gender and the Labor Market: What Have we Learned from Field and Lab Experiments? Labour Economics, 30(3), 32–40.

Babcock, L., Gelfand, M., Small, D. and H. Stayn (2006). Propensity to Initiate Negotiations: A New Look at Gender Variation in Negotiation Behavior. In: De Cremer, D., Zeelenberg, M. and J.K. Murnighan (Eds.). Social Psychology and Economics. Mahwah, New Jersey: Lawrence Erlbaum Associates, 239–262.

Babcock, L. and S. Laschever (2003). Women Don't Ask: Negotiation and the Gender Divide. New York, NY: Random House.

Babcock, L. Recalde, M.P. and L. Vesterlund (2017). Gender Differences in the Allocation of Low-Promotability Tasks: The Role of Backlash, American Economic Review, 107(5), 131–135.

Bayard, K., J. Hellerstein, D. Neumark and K. Troske (2003). New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data. Journal of Labor Economics, 2(4)1, 887–922.

Bertrand, M. (2011). New Perspectives on Gender, In: Ashenfelter, O. and D. Card (Eds.). Handbook of Labor Economics, Volume 4b, North-Holland, Great Britain.

Bertrand, M., Goldin, C. and L. F. Katz (2010). Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. American Economic Journal: Applied Economics, 2(3), 228–255.

Blau, F. D. and L. M. Kahn (2000). Gender Differences in Pay. Journal of Economic Perspectives, 14(4), 75–99.

Blau, F. D. and L. M. Kahn (2013). The Feasibility and Importance of Adding Measures of Actual Experience to Cross-Sectional Data Collection. Journal of Labor Economics, 31(S1), S17–S58.

Blau, F. D. and L. M. Kahn (2017). The Gender Wage Gap: Extent, Trends, and Sources. Journal of Economic Literature, 55(3), 789–865.

Buser, T., Niederle, M. and H. Oosterbeek (2014). Gender, Competitiveness, and Career Choices, Quarterly Journal of Economics, 129(3), 1409–1447.

Cameron, A. C and P.K. Trivedi (2010). Microeconometrics using Stata. Revised Edition, Stata Press.

Cabral, L. and A. Hortaçsu (2010). The Dynamics of Seller Reputation: Evidence from eBay, Journal of Industrial Economics, 58, 54–78.

Card, D., Cardoso, A.R. and P. Kline (2016). Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. Quarterly Journal of Economics, 131(2), 633–686.

Charness, G. and U. Gneezy (2012). Strong Evidence for Gender Differences in Risk Taking. Journal of Economic Behavior and Organization, 83 (1), 50–58.

Chan, J. and J. Wang (2017). Hiring Preferences in Online Labor Markets: Evidence of a Female Hiring Bias. Management Science, 64(7), 2973–2994.

Cook, C., R. Diamond, J. Hall, J. List and P. Oyer (2018). The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers. Natural Field Experiments 00634, The Field Experiments Website.

Croson, R. and U. Gneezy (2009). Gender Differences in Preferences. Journal of Economic literature, 47(2), 448–474.

Czibor, E., Claussen, J. and M. van Praag (2018), Women in a Men's World: Risk Taking in an Online Card Game Community. Journal of Economic Behavior and Organization, forthcoming.

Dittrich, M., Knabe, A. and K. Leipold (2014). Gender Differences in Experimental Wage Negotiations. Economic Inquiry, 52(2), 862–873.

Gerhart, B. and S. Rynes (1991). Determinants and Consequences of Salary Negotiations by Male and Female MBA Graduates. Journal of Applied Psychology, 76(2), 256–62.

Gneezy, U., Niederle, M. and A. Rustichini (2003), Performance in Competitive Environments: Gender Differences. Quarterly Journal of Economics, 118 (3), 1049–1074.

Goldin, C. (2014). A Grand Gender Convergence: Its Last Chapter. American Economic Review, 104(4), 1091–1119.

Goldin, C. and L. F. Katz (2016). A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation. Journal of Labor Economics, 34(3), 705–746.

Greene, W. (2004). The Behaviour of the Fixed Effects Estimator in Nonlinear Models. Econometrics Journal, 7, 98–119.

Hall, R. E. and A. B. Krueger (2012). Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Search. American Economic Journal: Macroeconomics, 4(4), 56–67.

Heckman, J.J. (1979). Sample Selection Bias as a Specification Error. Econometrica, 47(1), 153–161.

Hoisl, K. and M. Mariani (2017). It's a Man's Job: Income and the Gender Gap in Industrial Research. Management Science, 63(3), 766–790.

Horton, J.J. (2010). Online Labor Markets. In: Saberi, A. (Ed.) Internet and Network Economics. WINE 2010. Lecture Notes in Computer Science, Vol. 6484. Springer, Berlin, Heidelberg.

Horton, J.J. and T. Prasanna (2015). Labor Economists Get Their Microscope: Big Data and Labor Market Analysis. Big Data, 3(3), 130–137.

Kässi, O. and V. Lehdonvirta (2018), Online Labour Index: Measuring the Online Gig Economy for Policy and Research. Technological Forecasting and Social Change, Volume 137, 241–248.

Kuek, S.C, Paradi-Guilford, C., Fayomi, T., Imaizumi, S. and P. Ipeirotis (2015), The Global Opportunity in Online Outsourcing, World Bank Group, Washington, D.C.

Malone, T.W. and R.J. Laubacher (1998). The Dawn of the e-Lance Economy. Harvard Business Review, 76, 144–152

Malone, T.W. and R.J. Laubacher (2003). Inventing the Organizations of the 21st Century. Malone, T.W., Laubacher, R.J. and M.S. Scott Morton (Eds.), Cambridge, MA: MIT Press.

Nelson, J.A. (2015). Are Women Really More Risk-Averse than Men? A Re-analysis of the Literature Using Expanded Methods, Journal of Economic Surveys, 29(3), 566–585.

Niederle, M. and L. Vesterlund (2007). Do Women Shy Away from Competition? Do Men Compete Too Much? Quarterly Journal of Economics, 122(3), 1067–1101.

Neyman J. and E. Scott (1948). Consistent Estimates Based on Partially Consistent Observations. Econometrica, 16, 1–32.

OECD (2018), Gender Wage Gap (indicator). doi: 10.1787/7cee77aa-en (Accessed on 20 June 2018).

Pallais, A. (2014). Inefficient Hiring in Entry-Level Labor Markets. American Economic Review, 104, 3565–3599.

Reuben, E., Sapienza, P. and L. Zingales (2015). Taste for Competition and the Gender Gap Among Young Business Professionals. NBER Working Paper No. 21695

Straub, T., Gimpel, H., Teschner, F. and C. Weinhardt (2015). How (not) to Incent Crowd Workers - Payment Schemes and Feedback in Crowdsourcing, Business & Information Systems Engineering, 57(3), 167–179.

Williams, R. (2012). Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects. Stata Journal, 12 (2), 308–331.

Tables

Table 1 | Summary statistics for employers at the project level (Design phase)

	Total sample; *N*(total) = 257,111				Female employers; *n*(female) = 62,735				Male employers; *n*(male) = 172,877			
VARIABLES	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Dependent variables												
Budget proposed (Stage 1)	0.361	0.480	0	1	0.316	0.465	0	1	0.368	0.482	0	1
Budget (Stage 2)	111.1	1,147	0	137,412	77.12	964.2	0	124,920	119.5	1,169	0	137,412
Main variables of interest												
Employer female	0.244	0.429	0	1	1	0	1	1	0	0	0	0
Employer male	0.672	0.469	0	1	0	0	0	0	1	0	1	1
Employer gender unknown	0.084	0.277	0	1	0	0	0	0	0	0	0	0
Employer characteristics												
Employer experience	6.299	13.04	1	426	5.694	13.88	1	426	6.296	12.59	1	300
Share of projects in the same day & category where budget is revealed (exclusion variable)	0.127	0.192	0	1	0.123	0.189	0	1	0.127	0.191	0	1
Project characteristics												
Experience level required: Intermediate	0.696	0.460	0	1	0.721	0.448	0	1	0.692	0.462	0	1
Experience level required: Expert	0.163	0.370	0	1	0.131	0.338	0	1	0.172	0.378	0	1
Approximate number of hours required for the job	12.86	96.93	0.0133	12,690	9.576	77.92	0.0133	11,104	13.86	101.9	0.0140	12,690

Notes: The dependent variable in Stage 2, i.e., the amount of the proposed budget, is only observable for 92,759 observations. Out of those, 19,808 correspond to female workers, 63,678 to male employers and the rest to employers whose gender is unknown.

Table 2 | Summary statistics for employers at the level of wage bill proposals (Competition phase)

	Total sample; N(total) = 2,665,361				Female workers; n(female) = 533,848				Male workers; n(male) = 1,628,387			
VARIABLES	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Dependent variables												
Wage bill proposal made (Stage 3)	0.496	0.217	0	1	0.0515	0.221	0	1	0.049	0.216	0	1
Amount of wage bill proposal (Stage 4)	462.7	1,539	0.900	138,799	328.8	1,400	1.250	138,799	475.8	1,590	0.900	138,799
Main variables of interest												
Worker female	0.200	0.400	0	1	1	0	1	1	0	0	0	0
Worker male	0.611	0.488	0	1	0	0	0	0	1	0	1	1
Worker gender unknown	0.189	0.391	0	1	0	0	0	0	0	0	0	0
Worker characteristics												
Worker experience	623.3	1,997	1	30,116	342.5	949.2	1	10,470	527.4	1,185	1	12,957
Certificate of the worker in the platform	4.097	1.458	1	6	4.218	1.307	1	6	4.281	1.283	1	6
At least one worker's skill matches project description	0.613	0.487	0	1	0.604	0.489	0	1	0.679	0.467	0	1
Project characteristics												
Employer female	0.255	0.436	0	1	0.246	0.431	0	1	0.291	0.454	0	1
Employer male	0.665	0.472	0	1	0.631	0.483	0	1	0.673	0.469	0	1
Employer gender unknown	0.0802	0.272	0	1	0.0779	0.268	0	1	0.0795	0.270	0	1
Number of words in the project description	93.40	85.74	1	1,486	89.50	81.05	1	1,486	93.66	85.84	1	1,180
Files attached in the project description	0.197	0.397	0	1	0.200	0.400	0	1	0.201	0.401	0	1
Budget proposed	0.401	0.490	0	1	0.389	0.488	0	1	0.402	0.490	0	1
Experience level required: Entry	0.142	0.349	0	1	0.162	0.369	0	1	0.140	0.347	0	1
Experience level required: Intermediate	0.624	0.484	0	1	0.630	0.483	0	1	0.624	0.484	0	1
Experience level required: Expert	0.234	0.424	0	1	0.207	0.405	0	1	0.237	0.425	0	1
Approximate number of hours required for the job	17.90	122.0	0.0133	12,690	12.62	90.02	0.0648	12,690	18.31	126.2	0.0133	12,690
Average number of proposals per day (exclusion variable in Stage 3)	0.049	0.056	0.0079	1	0.051	0.059	0.008	1	0.049	0.054	0.008	1

Notes: The total number of wage bill proposals in Stage 3 (including those that a worker decides *not* to make, see Section II.B) is 53,779,126. Of those, 10,358,310 are made by female workers, 34,252,912 by male workers and the rest by workers whose gender is unknown.

Table 3 | Summary statistics for employers at the level of wage bill proposals (Agreement phase)

	Total sample; *N*(total) = 2,665,361				Female workers; *n*(female) = 533,848				Male workers; *n*(male) = 1,628,387			
VARIABLES	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Dependent variables												
Contract awarded (Stage 5)	0.0494	0.217	0	1	0.0708	0.256	0	1	0.0466	0.211	0	1
Agreed wage bill (Stage 6)	181.960	453.577	0	30768	141.771	320.968	0	24,984	193.007	483.114	0	30,768
Main variables of interest												
Worker female	0.200	0.400	0	1	1	0	1	1	0	0	0	0
Worker male	0.611	0.488	0	1	0	0	0	0	1	0	1	1
Worker gender unknown	0.189	0.391	0	1	0	0	0	0	0	0	0	0
Worker characteristics												
Number of words in the worker profile	134.2	125.0	1	2,658	133.2	123.7	1	2,141	126.6	115.0	1	1,660
Worker experience	623.3	1,997	1	30,134	342.5	949.2	1	10,476	527.4	1,185	1	12,958
Certificate of the worker in the platform	4.097	1.458	1	6	4.218	1.307	1	6	4.281	1.283	1	6
At least one worker's skill matches project description	0.613	0.487	0	1	0.604	0.489	0	1	0.679	0.467	0	1
Project characteristics												
Budget proposed	0.401	0.490	0	1	0.389	0.488	0	1	0.402	0.490	0	1
Experience level required: Intermediate	0.624	0.484	0	1	0.630	0.483	0	1	0.624	0.484	0	1
Experience level required: Expert	0.234	0.424	0	1	0.207	0.405	0	1	0.237	0.425	0	1
Amount of the wage bill proposal	462.7	1,898	0.900	138,799	328.8	1,626	0.900	138,799	475.8	1,934	0.900	138,799
Number of wage bill proposals	24.11	23.07	1	873	23.30	21.43	1	873	24.29	24.28	1	873
Employer characteristics												
Employer female	0.255	0.436	0	1	0.291	0.454	0	1	0.247	0.431	0	1
Employer male	0.665	0.472	0	1	0.631	0.483	0	1	0.673	0.469	0	1
Employer gender unknown	0.0802	0.272	0	1	0.0779	0.268	0	1	0.0795	0.270	0	1
Employer experience	5.588	11.51	1	426	6.105	13.12	1	426	5.531	11.19	1	426
Number of projects awarded by an employer in a given category (exclusion variable in Stage 5)	1.449	4.418	0	191	1.748	5.797	0	191	1.400	4.017	0	191

Notes: The dependent variable in Stage 6, i.e., the amount of the agreed wage bill, is only observable for 1,255,778 observations. Out of those, 270,758 correspond to female workers, 762,298 to male workers and the rest to workers whose gender is unknown.

Table 4 | Design: Employers choose to reveal the budget (Stage 1) and the amount of the budget (Stage 2)

	(1)	(2)	(3)	(4)
Stage:	Stage 1		Stage 2	
	Budget proposed	Log budget proposed by employer	Log budget proposed by employer	Log budget proposed by employer
Model:	Probit Heckman	OLS Heckman	OLS	OLS
Employer female	-0.075***	-0.016***	-0.018***	
	(0.014)	(0.006)	(0.006)	
Employer gender unknown	0.062***	-0.004	-0.002	
	(0.012)	(0.009)	(0.009)	
Experience level required: Intermediate	-1.048***	0.273***	0.247***	0.290***
	(0.016)	(0.017)	(0.014)	(0.011)
Experience level required: Expert	-0.473***	0.566***	0.555***	0.617***
	(0.016)	(0.042)	(0.041)	(0.021)
Log approximate number of hours required for the job	0.315***	0.833***	0.841***	0.739***
	(0.037)	(0.016)	(0.015)	(0.007)
Employer experience (log cumulative number of projects posted)	0.168***	-0.055***	-0.051***	-0.052***
	(0.016)	(0.006)	(0.005)	(0.010)
Share of projects in the same day & category where budget is revealed	0.660***			
	(0.015)			
Mill		0.039***		
		(0.012)		
Constant	-0.110	2.224***	2.265***	2.425***
	(0.088)	(0.032)	(0.029)	(0.082)
Day dummies	YES	YES	YES	YES
Category dummies	YES	YES	YES	YES
Country of employer dummies	YES	YES	YES	NO
Employer dummies	NO	NO	NO	YES
Observations	254,943	92,749	92,759	92,759
R-squared		0.848	0.848	0.941

Notes: Observations are at the level of projects. Regression coefficients reported. Robust standard errors clustered at the country of employer-level in parentheses in columns (1) to (3). Robust standard errors are clustered at the employer level in column (4). We use the *areg* command in column (4) to absorb the employer dummies.
*** p<0.01, ** p<0.05, * p<0.1.

Table 5 | Competition: Workers choose to make a wage bill proposal (Stage 3) and the amount of the wage bill proposal (Stage 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stage:	Stage 3			Stage 4			
Dependent variable:	Wage bill proposal made	Log amount wage bill proposal	Log amount wage bill proposal	Log amount wage bill proposal	Log amount wage bill proposal	Log amount wage bill proposal	Log amount wage bill proposal
Model:	Probit Heckman	OLS Heckman	OLS	OLS	OLS	OLS	OLS
Worker female	0.011***	-0.077***	-0.077***		-0.057***	-0.067***	-0.041***
	(0.002)	(0.005)	(0.005)		(0.002)	(0.002)	(0.001)
Worker gender unknown	-0.000	0.165***	0.165***		0.135***	0.135***	0.116***
	(0.002)	(0.003)	(0.003)		(0.002)	(0.002)	(0.002)
Employer female	0.046***	-0.018***	-0.016***	-0.005**			
	(0.003)	(0.004)	(0.004)	(0.003)			
Employer gender unknown	-0.013**	-0.004	-0.004	-0.002			
	(0.006)	(0.004)	(0.004)	(0.005)			
Worker experience (log cumulative number of wage bill proposals)	0.042***	0.024***	0.026***	0.009***	0.028***	0.028***	0.025***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Certificate of the worker in the platform	-0.010***	0.002*	0.002		0.002***	0.002***	0.004***
	(0.002)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
At least one worker's skill matches project description	0.275***	0.028***	0.037***	0.028***	0.021***	0.021***	0.007***
	(0.003)	(0.006)	(0.006)	(0.001)	(0.002)	(0.002)	(0.002)
Log number of words in the project description	-0.028***	0.082***	0.081***	0.053***	0.123***	0.123***	
	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)	
Files attached in the project description	-0.033***	-0.114***	-0.116***	-0.040***	-0.087***	-0.087***	
	(0.001)	(0.005)	(0.005)	(0.002)	(0.006)	(0.006)	
Budget proposed	0.008*	-0.626***	-0.626***	-0.378***	-0.549***	-0.555***	
	(0.004)	(0.012)	(0.012)	(0.021)	(0.007)	(0.007)	
Experience level required: Intermediate	-0.412***	0.161***	0.135***	0.088***	0.144***	0.144***	
	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)	(0.006)	
Experience level required: Expert	-0.045***	0.364***	0.361***	0.231***	0.366***	0.366***	
	(0.006)	(0.011)	(0.012)	(0.005)	(0.008)	(0.008)	
Log number of hours required for a project	0.013***	0.413***	0.413***	0.282***	0.370***	0.370***	
	(0.001)	(0.008)	(0.008)	(0.009)	(0.003)	(0.003)	
Average number of wage bill proposals made by a worker in a given day	3.364***						
	(0.129)						
Mill		0.116***					
		(0.007)					
Worker female interacted with budget revealed						0.026***	
						(0.003)	
Day dummies	YES	YES	YES	YES	YES	YES	YES
Category dummies	YES	YES	YES	YES	YES	YES	YES
Country of employer dummies	YES	YES	YES	YES	NO	NO	NO
Country of worker dummies	YES	YES	YES	NO	YES	YES	YES
Employer dummies	NO	NO	NO	NO	YES	YES	NO
Worker dummies	NO	NO	NO	YES	NO	NO	NO
Project dummies	NO	NO	NO	NO	NO	NO	YES
Constant	-1.132***	3.243***	3.331***	3.920***	3.479***	3.481***	4.907***
	(0.065)	(0.051)	(0.048)	(0.036)	(0.091)	(0.091)	(0.006)
Observations	53,779,126	2,665,361	2,665,361	2,665,361	2,665,361	2,665,361	2,665,361
R-squared		0.430	0.430	0.670	0.547	0.547	0.623

Notes: Observations are at the level of wage bill proposals. Regression coefficients reported. Robust standard errors clustered at the employer country level in parentheses in columns (1) to (4). Robust standard errors clustered at the employer level in parentheses in columns (5) to (6). Robust standard errors clustered at the project level in parentheses in column (7). We use the *areg* command in columns (4), (5), (6) and (7) to absorb the worker dummies (4), employer dummies [(5) and (6)], and the project dummies (7), respectively. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6 | Agreement: Conditional on a proposal being accepted (Stage 5), employer and worker agree on a wage bill (Stage 6)

	(1)	(2)	(3)	(4)	(5)
Stage:	Stage 5	Stage 6			
Dependent variable:	Proposal accepted	Log agreed wage bill	Log agreed wage bill	Log agreed wage bill	Log agreed wage bill
Model:	Probit Heckman	OLS Heckman	OLS	OLS	OLS
Worker female	0.098***	-0.005*	-0.003*	-0.014***	-0.041***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.002)
Worker gender unknown	-0.049***	-0.002	-0.000	0.033***	0.028***
	(0.008)	(0.003)	(0.002)	(0.001)	(0.003)
Employer female	-0.034***	-0.019***			-0.032***
	(0.004)	(0.005)			(0.006)
Employer gender unknown	0.025**	-0.054***			-0.050***
	(0.010)	(0.007)			(0.007)
Log number of words in worker profile	-0.018***	-0.010***	-0.007***	0.012***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Worker experience (log cumulative number of wage bill proposals)	-0.075***	-0.006***	-0.004***	0.005***	-0.002***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Certificate of the worker in the platform	0.258***	0.004***	0.005***	0.005***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
At least one worker's skill matches project description	0.066***	0.054***	0.035***	0.050***	0.046***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)
Budget proposed	0.014	0.103***	-0.001	-0.112**	0.106***
	(0.017)	(0.015)	(0.032)	(0.050)	(0.013)
Experience level required: Intermediate	0.047***	0.333***	0.382***	0.575***	0.345***
	(0.004)	(0.004)	(0.009)	(0.014)	(0.003)
Experience level required: Expert	0.115***	0.597***	0.719***	1.118***	0.612***
	(0.006)	(0.010)	(0.010)	(0.015)	(0.012)
Log amount wage bill proposal	-0.189***	0.648***	0.376***		0.673***
	(0.005)	(0.004)	(0.004)		(0.003)
Employer experience (log cumulative number of projects posted)	-0.368***	-0.078***	-0.064***	-0.088***	-0.075***
	(0.018)	(0.004)	(0.014)	(0.015)	(0.004)
Log number of wage bill proposals	-0.592***	0.107***	0.110***	0.207***	0.052***
	(0.004)	(0.009)	(0.005)	(0.008)	(0.005)
Log cumulative number of projects awarded by an employer in a given category	0.757***				
	(0.029)				
Mill		0.188***			
		(0.027)			
Day dummies	YES	YES	YES	YES	YES
Category dummies	YES	YES	YES	YES	NO
Country of employer dummies	YES	YES	NO	NO	YES
Country of worker dummies	YES	YES	YES	YES	NO
Employer dummies	NO	NO	YES	YES	NO
Constant	-0.590***	-0.628***	1.374***	2.414***	-0.463***
	(0.040)	(0.103)	(0.081)	(0.092)	(0.109)
Observations	2,664,701	1,255,457	1,255,609	1,255,609	1,255,609
R-squared		0.605	0.831	0.777	0.597

Notes: Observations are at the level of wage bill proposals. Regression coefficients reported. Robust standard errors clustered at the employer-country level in parentheses. We use the *areg* command in (3) and (4) to absorb the employer dummies. The number of observations in column (1), i.e., 2,664,701, differs from the number of observations in Table 5, columns (2) to (7), i.e., 2,665,361, because some observations are dropped in the estimation procedure (Probit). *** p<0.01, ** p<0.05, * p<0.1.

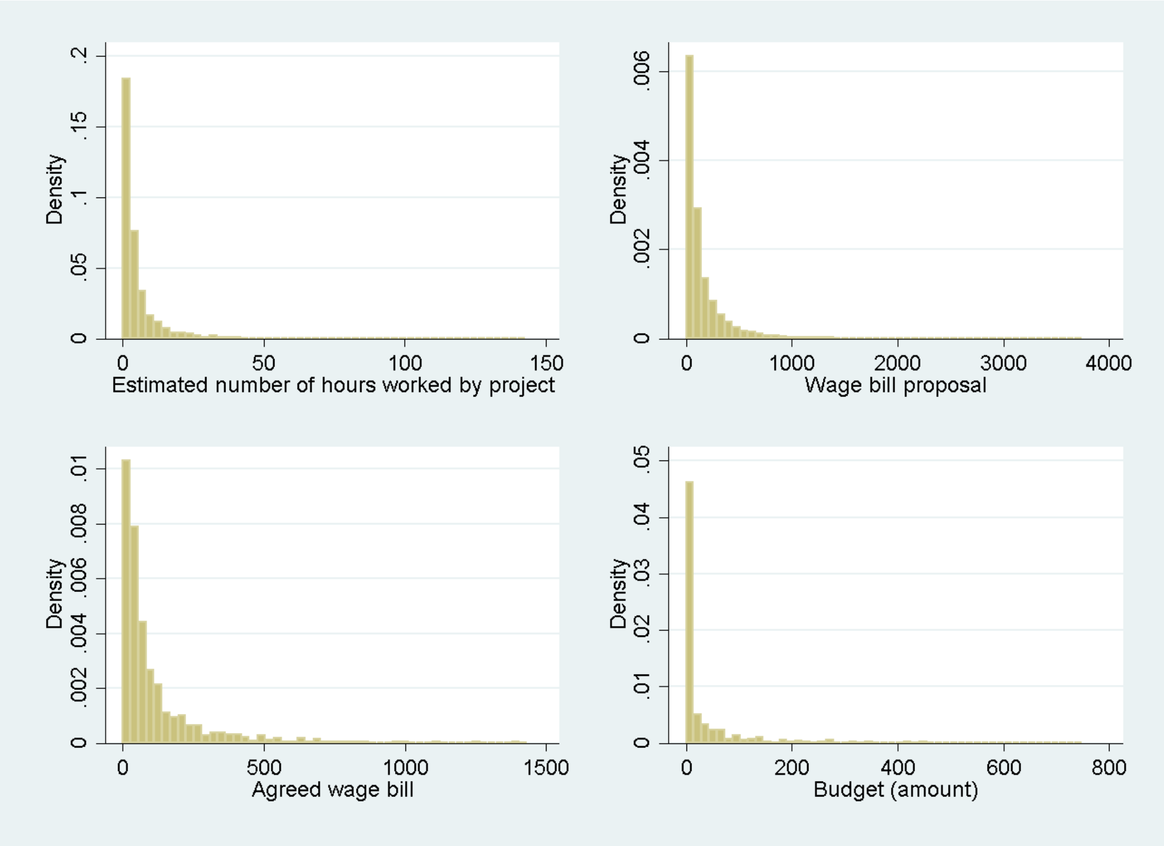
Appendix

Appendix 1 | Posted and completed projects by category

	(1)	(2)	(3)
Category	**Number of projects posted**	**Number of projects completed**	**Agreed wage bill (000€)**
Administrative	8,898	5,792	459.40
Business Support	14,859	6,794	998.77
Creative Arts	3,197	1,417	161.17
Design	68,574	39,288	4,217.24
Extraordinary	723	241	36.18
Marketing & PR	10,032	3,508	506.43
Mobile	5,602	1,491	931.40
Search Marketing	6,198	2,341	367.96
Social Media	5,273	2,052	201.23
Software Development	11,205	3,824	1,269.47
System	2,119	1,676	335.00
Translation	6,739	4,683	423.08
Tutorials	848	309	36.29
Video, Photo & Audio	18,574	9,302	1,185.09
Web Development	53,801	27,013	5,488.10
Writing	21,757	13,357	1,353.05
Unknown	18,860	11,897	2,082.24

Notes: For the sample period and by category, Columns (1) and (2) show the total number of posted projects and completed projects, respectively. Column (3) shows the total amount billed for the completed projects (in euros). Categories are pre-defined by PPH.

Appendix 2 | Distribution of Number of Hours per Project



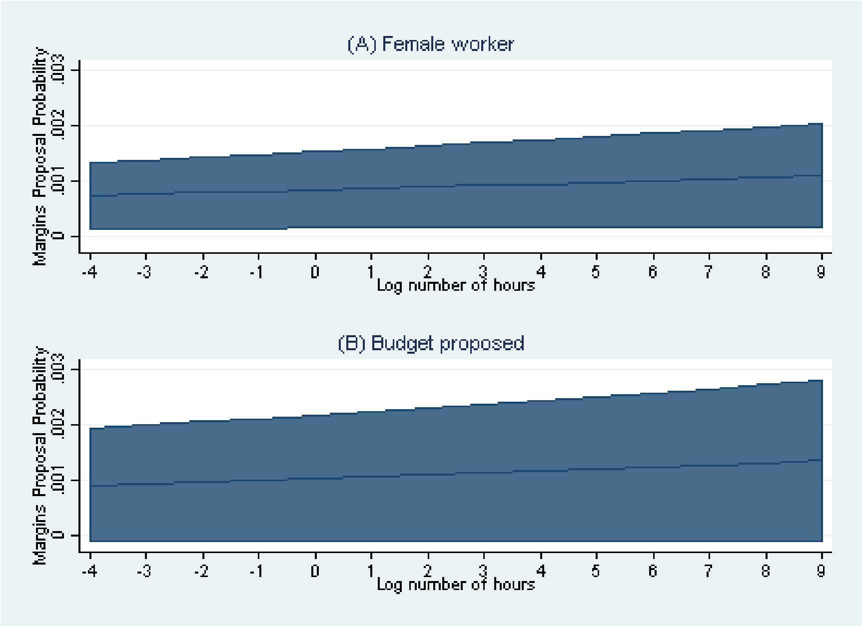
Notes: For the sake of clarity, we exclude projects beyond the 0.99 quantile of each variable.

Appendix 3 | Marginal effects at the mean after Probit regression

	(1)	(2)	(3)
Stage:	Stage 1	Stage 3	Stage 5
Dependent variable:	Budget revealed	Wage bill proposal made	Proposal accepted
Model:	Probit	Probit	Probit
Worker female		0.001**	0.004***
		(0.000)	(0.000)
Worker gender unknown		-0.000	-0.002***
		(0.000)	(0.000)
Employer female	-0.026***	0.003***	-0.001***
	(0.005)	(0.000)	(0.000)
Employer gender unknown	0.021***	-0.000	0.001**
	(0.004)	(0.001)	(0.000)
Log number of words in worker profile			-0.001***
			(0.000)
Worker experience (log cumulative number of wage bill proposals)		0.003***	-0.003***
		(0.000)	(0.000)
Certificate of the worker on the platform		-0.001***	0.010***
		(0.000)	(0.000)
At least one worker's skill matches project description		0.021***	0.002***
		(0.000)	(0.000)
Log number of words in the project description		-0.003***	
		(0.000)	
Files attached in the project description		-0.002***	
		(0.000)	
Budget proposed		0.001*	0.001
		(0.001)	(0.001)
Experience level required: Intermediate	-0.362***	-0.042***	0.002***
	(0.006)	(0.001)	(0.000)
Experience level required: Expert	-0.163***	-0.002***	0.005***
	(0.006)	(0.001)	(0.000)
Log number of hours required for a project	0.109***	0.001***	
	(0.013)	(0.000)	
Log amount wage bill proposal			-0.007***
			(0.000)
Employer experience (log cumulative number of projects posted)	0.058***		-0.014***
	(0.006)		(0.001)
Log number of wage bill proposals			-0.022***
			(0.000)
Share of projects in the same day & category where budget is revealed	0.229***		
	(0.011)		
Average number of wage bill proposals made by a given worker on a given day		0.268***	
		(0.008)	
Log cumulative number of projects awarded by an employer in a given category			0.028***
			(0.001)
Observations	254,943	5,323,042	2,664,701

Notes: Observations are at the level of projects in column (1) and at the level of wage bill proposals in columns (2) and (3), respectively. Marginal effects at means reported. Robust standard errors clustered at the employer country level. For computational limitations, in column (2) we use a random sample of the 10% of total observations. All regressions include day, category and employer country dummies. Columns (2) and (3) additionally include worker country dummies.
*** p<0.01, ** p<0.05, * p<0.1.

Appendix 4 | Marginal Effects of (A) Female Workers and (B) Budget Proposed on the Probability of Submitting a Wage Bill Proposal, by Project Size



Notes: The figure shows the marginal effects at representative values of project size (number of hours) for (A) *WorkerFemale =1* and (B) *BudgetProposed=1* on the probability of submitting a wage bill proposal in the competition phase (Stage 3). The horizontal axis indicates project size as given by the log number of hours of a project. The vertical axis indicates the marginal effects on the probability of making a proposal. We indicate 95% confidence intervals. We use the *marginsplot* command in Stata to create this figure. We obtained this figure using a random sample consisting of 5,323,042 observations to reduce the computational burden. Part (A) of the figure suggests that the marginal effect of *WorkerFemale =1* on the probability of submitting a wage bill proposal is positive and small in magnitude, i.e., it does not exceed 0.21 percentage points. It slightly increases in project size. Part (B) suggests that the marginal effect at the means of *BudgetProposed*=1 never exceeds 0.3 percentage points and is slightly increasing in project size.