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WHAT DETERMINES PRICE IN PLATFORM WORK?

An empirical study on the impact of ratings, experience, and duration

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April 2021

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 730998

Abstract

Platform work is a fast-growing form of non-standard work characterised by an online platform that intermediates paid services. Among the main concerns discussed in the platform work literature at present are fair pay, ratings, and algorithmic management. However, very little empirical evidence has attempted to shed light on these issues.

This report builds on a data set of platform worker profiles (n=1,420) retrieved by webscraping a German labour platform for cleaning services. This platform allows workers to set their hourly price, allowing analysis to better understand what determines price for platform workers.

Ratings are found to be a statistically significant, but economically insignificant, predictor of price. The most likely reason for this is that ratings are very inflated; essentially all platform workers are rated from 4-5. Experience is found to be statistically significant predictor of price; for every 100 tasks completed, hourly wages rise 2-4%. Duration on the platform is a significant and stronger predictor of price, as people who have been on the platform for longer earn more. This may be related to the importance of perceived trustworthiness for platform workers, whom clients invite into their homes to perform services. Gender and unemployment are also found to be significant, as men earn 3-4% less hourly than women, and an additional 1% unemployment reduces hourly earnings about 5%.

The findings suggest that ratings and reputation mechanics are an important topic for platform workers' earnings. The interface and design choices of platforms have real-world impacts on platform workers, which should elevate them as consequential issues in policy discussions.

Acknowledgements

I would like to thank, in no particular order, the following individuals for their invaluable feedback and discussions over the course of writing this paper: Hannah Johnston, Janine Berg, Six Silberman, Sara Baiocco, Mattia Di Salvo, Leonie Westhoff, Andreas Haupt, Daniel Gros, Karolien Lenaerts, and Stephanie Steinmetz.

I would further like to thank Annarosa Pesole and Uma Rani for their approval to use these data, which I gathered on the basis of an earlier project in cooperation with the Joint Research Centre. The data will also appear in their forthcoming European Commission Working Paper 'How many online workers? Estimated based on selected online web-based and location-based platforms'.

Contents

1. Introduction

Data on platform work are essential to understand the phenomenon, but good data are hard to come by for a number of technical and theoretical reasons.[34] This shortcoming is all too evident in efforts to define and measure the platform economy (e.g. the number of platform workers), which scholars have been attempting for years. Conceptual challenges in this task include definitional complexity and a lack of standardised terminology. On the technical side, data on platform work is not or cannot be gathered in most of the ways that data on other forms of work can be, such as national labour surveys and administrative reporting (Riso, 2019; Kilhoffer *et al.*, 2020).

This focus on the whole landscape of platforms is understandable; after all, the entire platform economy is more impactful than any single platform. Still, data on the platform economy are composed of data on individual platforms. While understanding the forest remains the ultimate goal, we can certainly gain from examining individual trees. This has a number of advantages, foremost of which is feasibility. Even though platforms are extremely diverse, better understanding a single platform can give important clues to how platform business models impact the workers.

This study attempts to shed light on certain factors about a particular platform – particularly, the relationship between a platform worker's characteristics (rating, gender, experience, etc.) and their earnings. This is relevant for decent working conditions, algorithmic management, and fairness in platform design.

Box 1: Selected platform description

The selected platform offers cleaning services, primarily in clients' homes. While based in and originating in Germany, it has expanded to other EU countries.

The selection process begins when a client enters a location (zip code), date, and time of day, then sees a list of candidate platform workers available at that time and place. The client sees each candidate's name, gender, average rating, experience (number of cleanings), duration (time since registering on the platform), and price per hour (which the workers themselves choose).

The client can then select a platform worker, who accepts or rejects the client's work offer. Upon acceptance, client and platform worker are put in contact to arrange logistics, and the platform worker meets the client and cleans for a specified number of hours. The client can rate the worker if they wish, and the worker's profile is updated to reflect their new average rating and experience. The service can be one-off or recurring.

Rather than relying on administrative data, surveys, or other more common methodologies, this case study uses data web-scraped in January and February 2020 from a German **cleaning platform**. This platform falls into a category of platform work sometimes called 'on-location' or 'location-dependent' (Eurofound, 2018; Brancati *et al.*, 2019).

A primary reason for selecting this platform is the pricing model. Unlike many on-location platforms, such as the big players offering personal transportation (Uber, Taxify) or food delivery (UberEats, Deliveroo, TakeAway), the selected platform allows platform workers to set their own hourly prices. Furthermore, many 'handyman' or multipurpose platforms intermediate an array of services, which makes it more difficult to compare similar work. By contrast, the selected platform only offers cleaning services.

In short, the characteristics of the selected platform allow us to gather data on and empirically explore policy-relevant research questions concerning prices and earnings on platform work. This

34 See discussion in Kilhoffer (2020a).

report aims to understand how platform workers set their price, and how signals visible to clients and platform workers impact this decision.

2. Theory

The analysis builds on **signalling theory**, which focuses on information asymmetries between at least two different market sides during the initiation of transactions. Platforms are multi-sided markets, making them an appropriate subject to apply the theory.

Sellers of goods and services know more about what they sell than clients, creating an information asymmetry. Traditional business transactions occur face-to-face, at least initially, which helps clients get a clearer idea of what they are purchasing, while establishing rapport between parties. This is usually not the case in platform work, and is not possible in many transactions occurring exclusively online (e.g. hiring a freelancer to design a graphic on 99Designs or UpWork). This creates an asymmetric information problem that platforms and platform workers must address.

Sellers can help to mitigate the information asymmetry and assure prospective clients by signalling the quality of their product service with descriptions, guarantees, warranties, or branding (Spence, 2002). Signals can be *conventional* (e.g. self-descriptions, promises), *handicap* (a product guarantee or well-crafted CV), or *index*. Index signals rely on some form of confirmation through an independent third party that used or experienced the product or service (Teubner *et al.*, 2017), and are generally considered the strongest type of signal (Aiken & Boush, 2006). The data scraped from the selected platform include several index signals:

1. average client rating;
2. number of jobs completed (experience);
3. duration on platform.

The first topic of interest is **client ratings** for platform workers. Ratings, typically shown as a number of stars between 1 and 5, are a critical component of platform work and online interactions more generally, and have become a **ubiquitous factor in addressing information asymmetry** (Belleflamme & Peitz, 2018). Van Doorn (2017: p. 903) writes:

> … *ratings have become a major decentralised and scalable management technique that outsources quality control to customers of on-demand platforms, creating a generalised audit culture in which service providers are continually pushed to self-optimise and cater to the customer's every whim.*

Ratings are essential to understanding how Uber created a business model where clients willingly enter a complete stranger's car. Caretaking, 'handyman' and cleaning platforms must go a step further, as clients invite strangers into their homes with or without supervision.[35]

For the service providers, **ratings are extremely consequential**. Platform workers' ratings can serve as a threshold for satisfactory work; Uber previously 'deactivated' drivers who failed to maintain a 4.6 out of 5 (Cook, 2015). Ratings attract or deter prospective clients, who primarily rely on reviews of earlier work to choose a platform worker (De Groen & Kilhoffer, 2019). Thus, ratings matter a great deal for platform workers' income and future job prospects (Huws *et al.*, 2019; Kilhoffer *et al.*,

35 Note that ratings are not the only risk mitigating factor for most platforms. For example, the selected platform offers clients insurance for property damaged during the cleaning.

2020). They also play a role in discrimination. For example, a worker's ethnicity might negatively impact their ratings (Ye *et al.*, 2017), or improve trust to counteract biases (Cui *et al.*, 2017).

Rating systems also provide an important source of **network effects**. The more platform workers on a platform, and the more ratings they have, the better informed clients are in their purchasing decisions. Rating systems are therefore part of self-reinforcing mechanisms that cause successful platforms to become more successful at the expense of smaller rivals (Belleflamme and Peitz, 2018). Similarly, within a single platform, a few platform workers with many reviews and high ratings are likely to edge out others, thereby attracting ever more clients in the future.

In spite of their importance, **rating systems are imperfect**. For example, Zervas et. al describe **rating inflation**, finding that 95% of AirBnB properties have an average rating between 4.5 and 5 stars, while virtually none have 3.5 or lower (2015). Wired Magazine described a situation familiar to many Uber users – a white-knuckle, harrowing ride through the city, which they rated a five star experience (Kane, 2015). Online marketplaces contain reviews that may be sincere, malicious, or fraudulent (Kaghazgaran *et al.*, 2017).

In platform work, five star reviews seem to be the default, while only the most unsatisfied clients leave one star reviews.[36] In previous interviews, workers of the selected platform suggested that below a four star rating, clients would never hire them (Eurofound, 2018). It is therefore unsurprising that platform workers and their advocates continue to call for more transparent and contestable review systems (Berg *et al.*, 2018).

Because ratings are important for both the platform (versus other platforms) and the platform workers themselves, I investigate **the relationship between average ratings and hourly price**. For the reasons explained above, and empirical evidence on how various signals translate to price (Edelman & Luca, 2014), **higher ratings are expected to increase the hourly price** a platform worker requests.[37]

H1: *Higher average ratings are positively correlated with hourly price.*

An additional index signal is **the number of completed tasks**. This serves to demonstrate a platform worker's experience, signalling trustworthiness and capacity to perform services. Some measure of experience is likely to be very important for platform workers, whom (on this platform) clients cannot select on the basis of more detailed job histories provided in a CV or similar.

H2: Higher experience is positively correlated with hourly price.

Next, **longer duration on the platform** is likely to signal that a platform worker is an established member of the community, which could impact the price a platform worker can successfully charge. For example, a platform worker who began yesterday is probably more likely to be fraudulent, as very little time has passed allowing fraud or malign intentions to be uncovered. Moreover, longer duration on the platform signals higher social capital, which may increase clients' satisfaction (Huang *et al.*, 2017; Teubner *et al.*, 2017).

H3: Longer duration on the platform is positively correlated with hourly price.

Finally, I expect that the number of completed tasks impacts how clients perceive the value of ratings, and thus explore an interaction effect between the average rating score and the total number of ratings. Consider two platform workers, each with an average five-star rating, but one having completed a single task, and one having completed a hundred. The latter would signal a consistent record of success and experience, whereas the former has too small a sample size to draw any strong con-

36 Two additional points on this note. First, some interviewed platform workers of the selected platform indicated that satisfied clients sometimes leave a four-star review, either not understanding or not caring that this greatly harms the worker. Some interviewees further described receiving reviews from elderly clients who misunderstood the star system. The written review was a glowing recommendation, but the client left a single star, apparently not understanding that this is the worst possible review.

37 On the other hand, platform workers, particularly those with more general skills (e.g. cleaning), have limited ability to set rates (De Groen & Kilhoffer, 2019). This would indicate that the size of the effect is not expected to be very large.

clusions.[38] With this theoretical grounding and empirical support (Gutt & Herrmann, 2015), I propose:

H4: The positive wage return to ratings increases with the number of tasks a platform worker has completed.

The expected relationships are summarised in Table 1.

Table 1. Summary of expectations for independent variables

Variable	Hypothesis	Models	Impact on Price
Rating	1	1, 9, 13	+
Experience	2	2, 10, 13	+
Duration	3	3, 11, 13	+
Interaction (rating*experience)	4	4, 12	+

* + indicates I expect a positive correlation between the independent and dependent variables.

I rely on four control variables: gender, unemployment, GDP per capita, and location (NUTS-3 region). Most general and platform work literature suggests that men earn more than women, which is also my expectation (Cook *et al.*, 2018; Aleksynska *et al.*, 2019). I also expect that areas of Germany with lower unemployment, higher GDP per capita, and higher living costs are associated with higher price per hour.[39] The main tool of analysis is ordinary least squares (OLS) linear regression.

2.1 Assumptions

A number of assumptions underlie this analysis. While those listed below are not exhaustive, they are useful to simplify the complex interactions between platform workers and clients in this online marketplace.

1. The platform operates on a hedonic price model, meaning that marketable features will be reflected in market prices (Rosen, 1974).
2. Clients and platform workers are aware that rating, experience, and duration signal the quality of services offered.
3. Platform workers charge the highest price per hour that allows them to continue finding work.
4. Clients seek to maximise the quality of services received and minimise price paid.

38 Or as Germans would say, *'Einmal ist keinmal'* – approximately 'Once is never'.

39 Unemployment data are from Eurostat representing NUTS-2 region in 2019. GDP per capita data are from Eurostat representing NUTS-3 region in 2019. Location is a categorical variable for NUTS-3 region, derived from the zip-code (*Postleitzahl*) used during webscraping.

3. Methodology

3.1 Data collection

To gather the data, I used Python to develop a webscraping programme.

Box 3: Webscraping description
Webscraping is a means of gathering data from websites. Webscraping typically makes use of automated tools developed with programming languages to extract data from webpages. In principle, anything that can be viewed online can be webscraped using a variety of techniques. Unstructured text, structured data, images, and anything else contained on a website can be retrieved.
Source: Kilhoffer (2020b: p. 8).

Webscraping has a number of pros and cons,[40] so researchers must be wary of ethical, practical, and legal restrictions on the practice. For example, webscraped data can be noisy, and not all websites are possible to scrape due to CAPTCHA, rate limiting, log-in requirements, etc. Nevertheless, webscraping can help equalise what researchers, policy-makers, and the platforms themselves know about their business models.

Typically, webscraping with Python uses the libraries Requests and BeautifulSoup, which is relatively quick and easy. However, the selected platform was unsuited for this method. More specifically, the platform's website does not list workers unless one specifies a date, time, and location. At this point, the website displays a list of workers who have made themselves available at this time and place. In testing, I was unable to recreate the request headers necessary to retrieve worker data using the website's API,[41] so I relied on a slower webscraping method.

With the goal of attaining a comprehensive dataset of workers on the platform, I used the Python library Selenium. Selenium is a tool for automating web browsers, primarily used for testing web applications, but it can also be used for webscraping. The main downside is that it is significantly slower and more computationally intensive than alternative methods.

I used Selenium to automate a web browser, simulating a human requesting available platform workers at various locations, dates, and times, and writing the data to CSV files. The process required a few weeks and took place in late January and early February 2020. I observed polite scraping protocol, placing delays between requests so as to not spam the platform's servers too frequently. I also ensured that the data were scraped and handle in accordance with the European Parliament's GDPR guidelines on webscraping.[42]

The webscraping programme searched all German zip codes at different dates and times. This aimed to ensure that platform workers would be found even if they are only sporadically available, such as only on weekends, or at certain times of day. Even so, only platform workers who made themselves available to work on the searched days and times could be retrieved. If they were registered on the platform but selected no dates to be available, they would not be found. Similarly, if a platform worker was taking a long break from the platform, they could not be retrieved.

40 See discussion in Kilhoffer (2020b).

41 Application programming interface.

42 The data gathered cannot be linked to a natural person; they do not contain last names, addresses, birthdays, emails, or anything else typically classified as protected, personal data. See European Parliament resolution (2016/2225(INI)) (European Parliament, 2017).

3.2 Pre-processing

The data needed to represent a single platform worker per row for analysis. Thus, we needed to merge and de-duplicate all of the CSV files created during webscraping. In some cases, the same platform worker was available in a number of zip codes, all days of the week, and virtually all times of day. Other platform workers were only sporadically available.

Exactly de-duplicating could not be performed using all columns of data, as certain aliases turned out to be common, and the scrape took place over a few weeks. I deliberately retrieved no worker ID number or other data that could definitively be linked to a person. In practice, this meant that some platform workers would have multiple rows where they were potentially listed with different numbers of completed cleanings, ratings, or durations. In exceptional cases, I had to manually check that workers with the same name and locations were not the same person. I could not be certain of six cases, where a row may or may not represent a duplicate of another person. These were removed from the dataset. Next, I added the NUTS-3 region for each platform worker based on zip-code searched.

3.3 Describing the data

The data consist of 1,420 observations, each representing a unique platform worker. Each worker has an alias, average rating, experience (count of completed assignments), duration on platform, hourly price, gender, and zip code.[43]

The average rating is a value from 1-5 to a single decimal place, or a blank if no client had yet left a rating. Experience was given as a whole number greater than five, except for those who had not yet completed five assignments; these were listed as ‘<5’.

The duration on the platform is listed in one of five categories: new, 1-6 months, 6-12 months, 1-3 years, or greater than 3 years. Hourly price is given in Euros and cents, while gender was given as male or female[44] based on the avatar displayed.

Table 2 Descriptive overview of continuous variables

	Count	Mean	Std.	Min.	25%	50%	75%	Max.
Price (€)	1,420	18.3	3.7	10.0	16.2	16.6	19.9	45
Rating (1-5)	1,065	4.7	0.4	1.0	4.6	4.8	4.9	5
Experience (# of jobs)	947	152.3	266.3	5	20	53	154	2,456

We see that hourly price is known for all 1,420 platform workers in the data. Average rating was known for 1,065, while the website displayed a blank for the remainder. In 947 cases, experience (the number of completed tasks) was listed as an integer. I discuss the treatment of these missing data below.

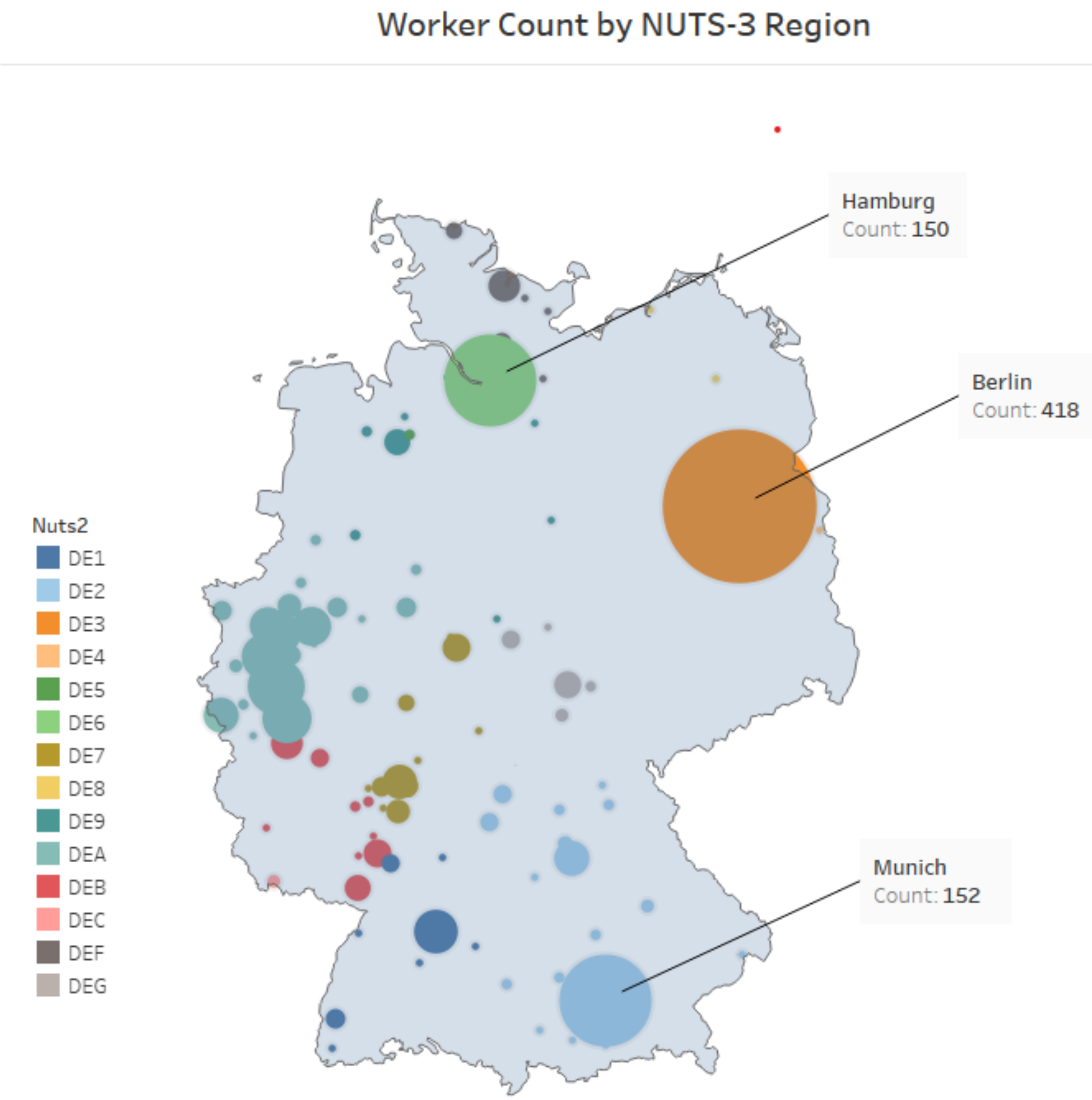
3.4 Analysis

Location data reveal platform workers are concentrated in the most urban areas of Germany (Figure 1). Berlin alone has almost 30% of all platform workers. The tendency for more activity in urban areas is unsurprising; other forms of on-location platform work are thought to be similar (Kilhoffer *et al.*, 2020).

43 From the search query used in the web-scraping programme.

44 Later in 2020, the platform began displaying profile pictures. This was not the case at the time of the scrape; all platform workers had either a generic female or male avatar.

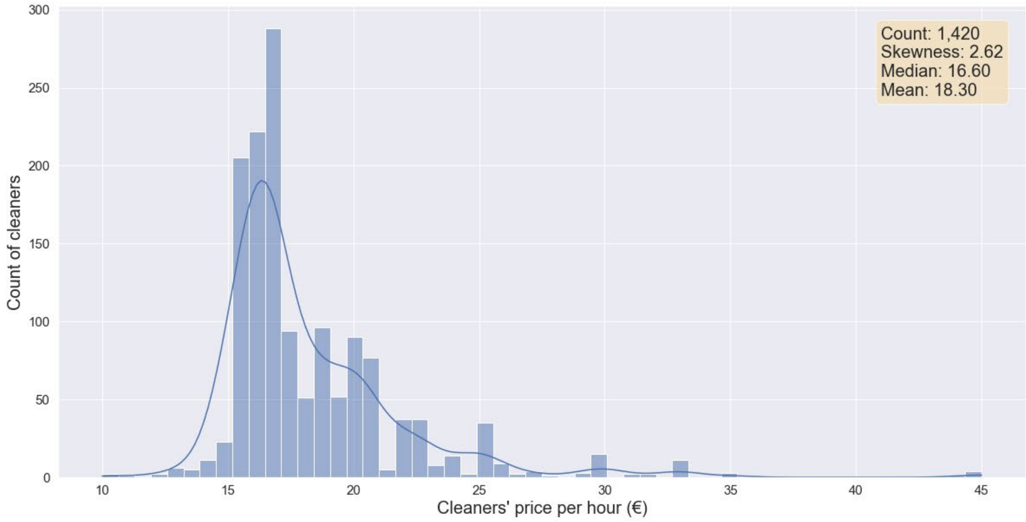
Figure 1. Distribution of platform workers in Germany



Note: The colour of each circle represents the NUTS2 region. Each NUTS-3 region with at least 2 platform workers has a circle shown. Larger circles indicate more platform workers.

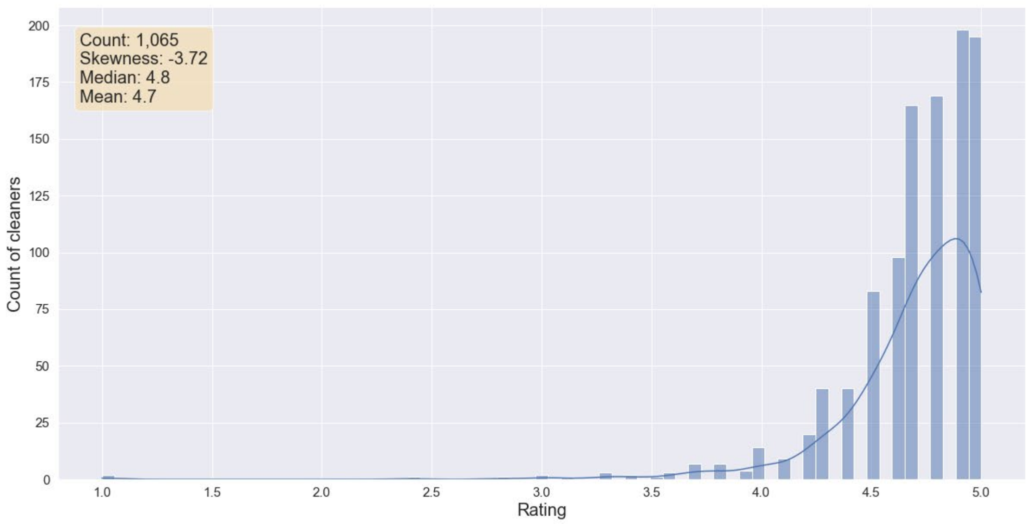
As shown in Figure 2, the distribution of prices has a long right tail with high skewness. A few outliers are notable here. While the mean price is 18.30 EUR per hour, and the 99th percentile is 33 EUR per hour, five workers charge over 44.00 EUR. These are not expected to be illustrative of larger trends; in fact, two of these individuals have virtually no experience and may not be setting realistic prices. To remove outliers, I calculate the z-score for price, then excluding observations with z-scores greater than 3.

Figure 2. Price histogram



The first explanatory variable is rating. Figure 3 shows a long left tail, indicating that lower ratings are very unusual, as discussed in the Theory section. Only 3.2% of the observations (34/1066) have a rating below 4, and the first percentile is 3.4. Exactly two people (0.14%) have a one-star rating. I therefore trim these outliers below the first percentile and leave NAs[45] in place.

Figure 3. Rating histogram



As discussed above, I assume that rating is related to price in two ways: having any rating, and the magnitude of the rating. In other words, there is a price penalty for having no rating, and there is a price reward for having a higher rating. In order to test both with the same variable, and to avoid excluding NAs from the analysis, I create an interaction variable.

First, I use a dummy variable, which is 1 if a cleaner has no rating, and 0 otherwise. Second, I replace NAs in the rating column with 0.5.[46] Third, I calculate the rating interaction as follows:

45 Not Applicable, or simply missing data.

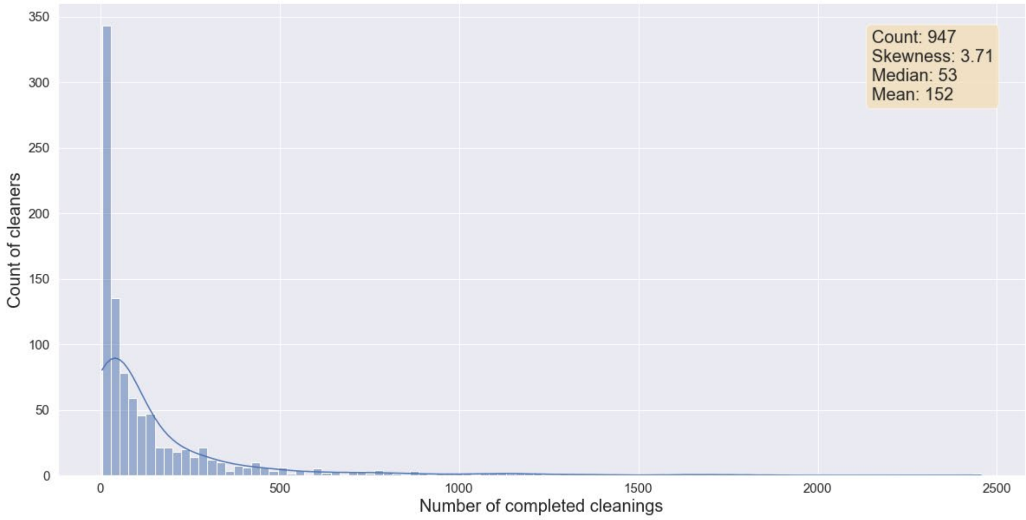
46 The value chosen to replace NA with does not matter, as it will be multiplied by 0.

Rating interaction = rating dummy + (1 – rating dummy) * (rating + 0.5)

In effect, this assigns a 1-star rating to those without a rating, while giving workers with a rating a 'bonus' of 0.5.

Moving to experience, Figure 4 shows the distribution, dropping all observations where the number of completed cleanings is '<5'.

Figure 4. Experience histogram



Before proceeding, I must handle the cleaner experience data shown as '<5'. For the moment, I replace '<5' with 2, being the mean of possible values: 0, 1, 2, 3, and 4. The new distribution is shown in Figure 5.

Figure 5. Experience histogram ('<5' replaced with 2)

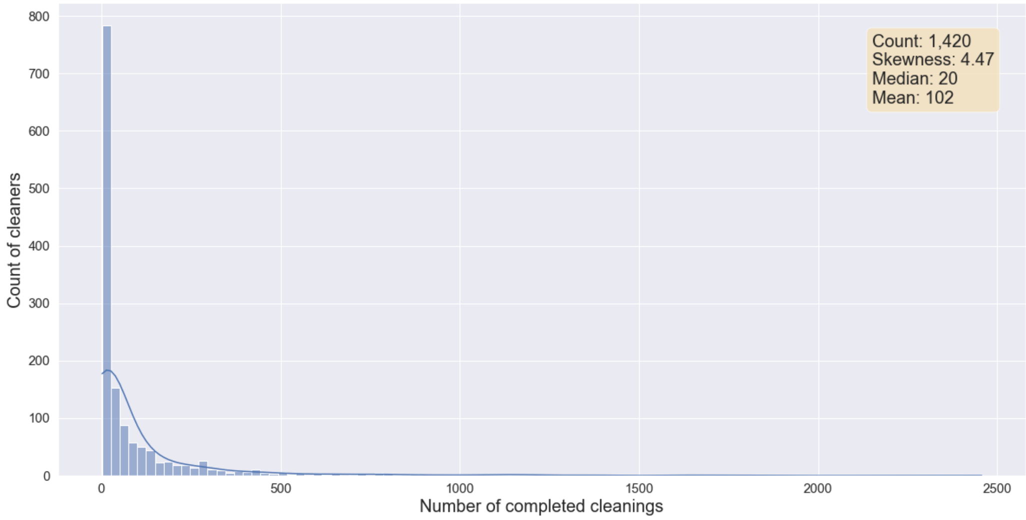


Figure 5 again shows an extremely long right tail and high skewness. The most experienced worker is an individual who has completed 2,456 tasks – far exceeding the second most experienced worker at 1,823. I thus remove outliers by excluding rows where the z-score for experience is greater than 3.

Similar to the rating variable, I assume that experience is related to price in two ways: having any (not '<5') experience, and the magnitude of experience.

I treat the experience variable similarly to rating. First, I create a dummy variable, which is 1 if a cleaner's experience is '<5', and 0 otherwise. Second, I replace '<5' in the experience column with 2. Third, I calculate the experience interaction as follows:

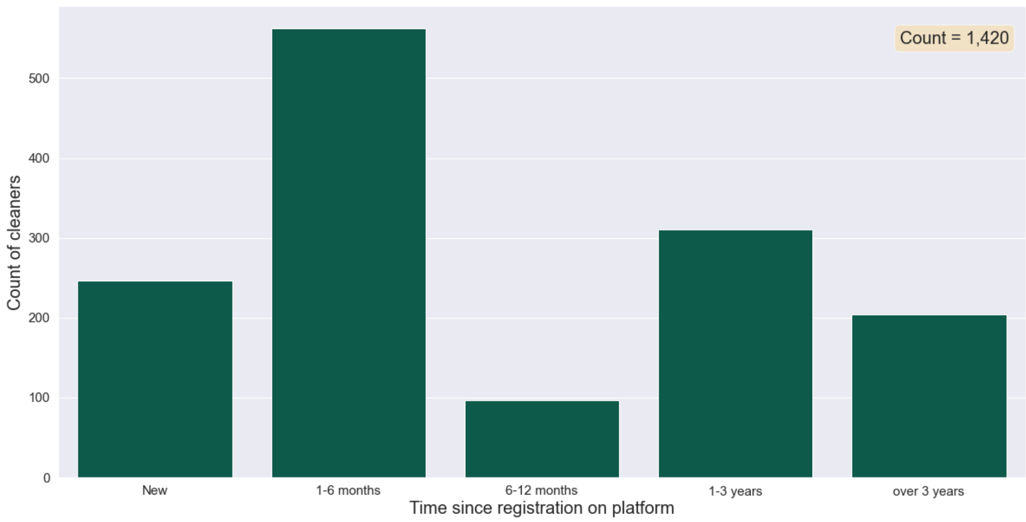
Experience interaction = experience dummy + (1 – experience dummy) * (experience + 5)

In effect, this assigns an experience of 1 to those who have less than five cleanings, while giving those with five or more cleanings a 'bonus' of 5.

While this strategy is not perfect, it does allow us to avoid excluding a large part of the dataset, while accounting for both the *presence of the information* (on rating and experience) and the *magnitude of the information*.[47]

As shown in Figure 6, duration is given in five categories. In order to compare how increasing levels of duration affect price in the regression, I set the reference level of the duration variable to 'New'.

Figure 6. Duration box plot

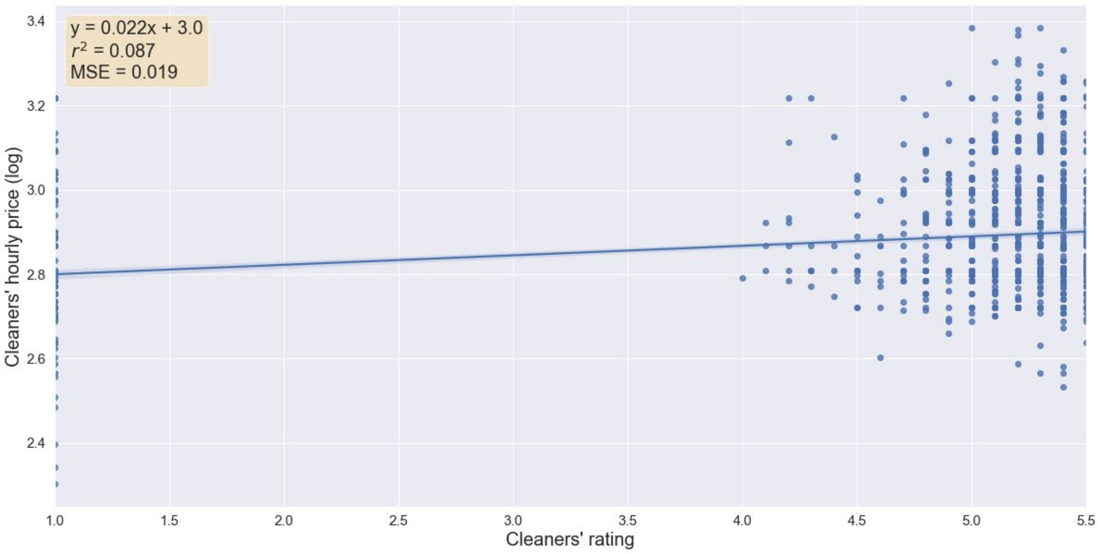


3.4.1 Bivariate analysis

Before running the full models, it is useful to check bivariate correlations between the independent and dependent variables. The first is rating, as shown in Figure 7, and corresponding to Hypothesis 1.

47 Alternative strategies would result in a smaller dataset or require imputing missing values. On the latter, attempts to impute missing values proved difficult and resulted in less precise models. Unfortunately, the dataset is not of a sufficient size, and lacks columns that may help with the imputation.

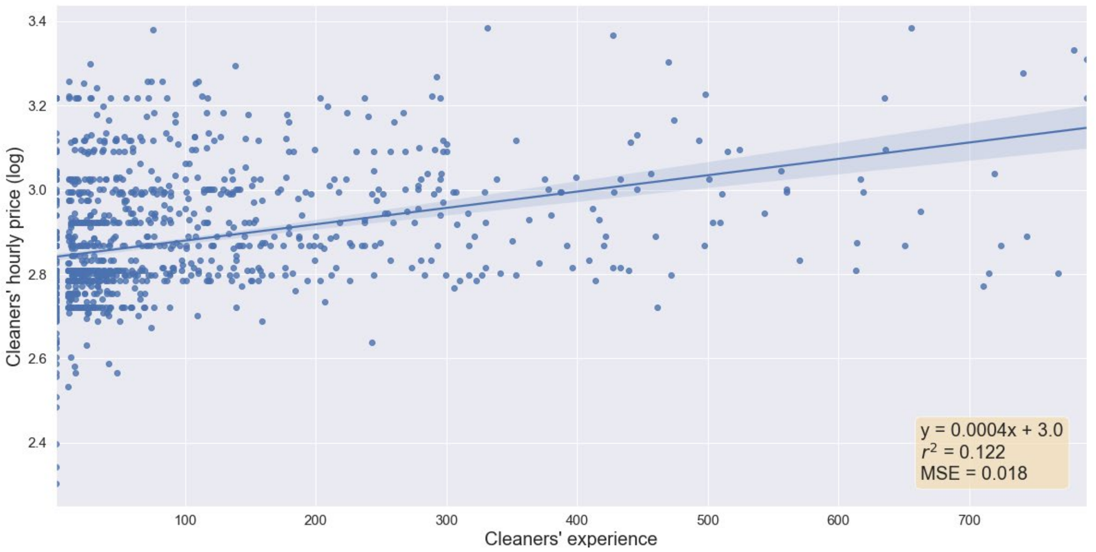
Figure 7. Cleaners' rating and price



Note: Cleaners' rating refers to the modified variable described above.

It does appear that people with higher ratings tend to have a higher price. Next, I plot cleaners' experience and price, as per Hypothesis 2.

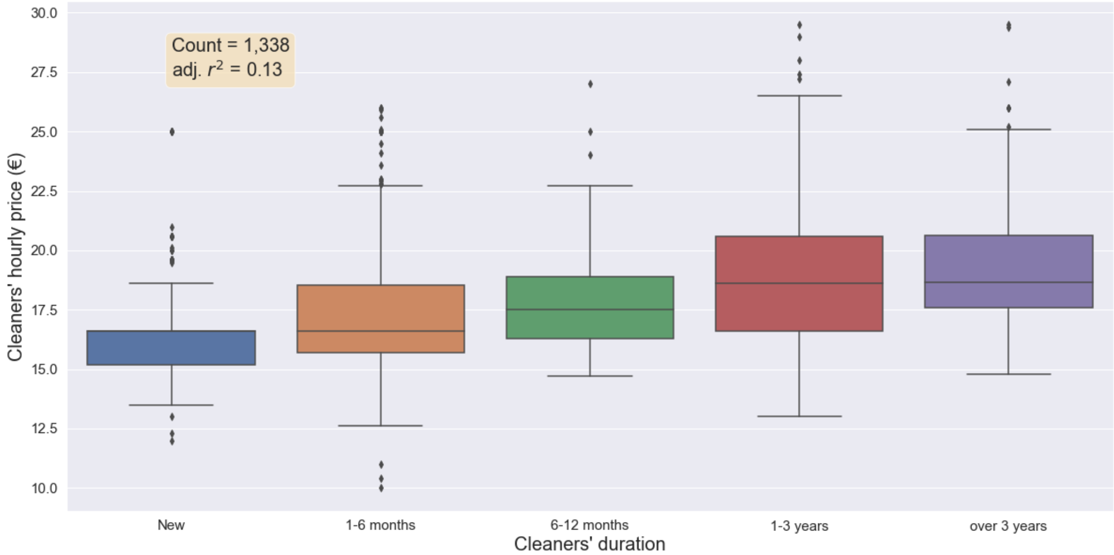
Figure 8. Cleaners' experience and price



Note: Cleaners' experience refers to the modified variable described above.
Source

Cleaners with more experience do seem to have a higher price. Next, I plot cleaners' duration and price, as per Hypothesis 3.

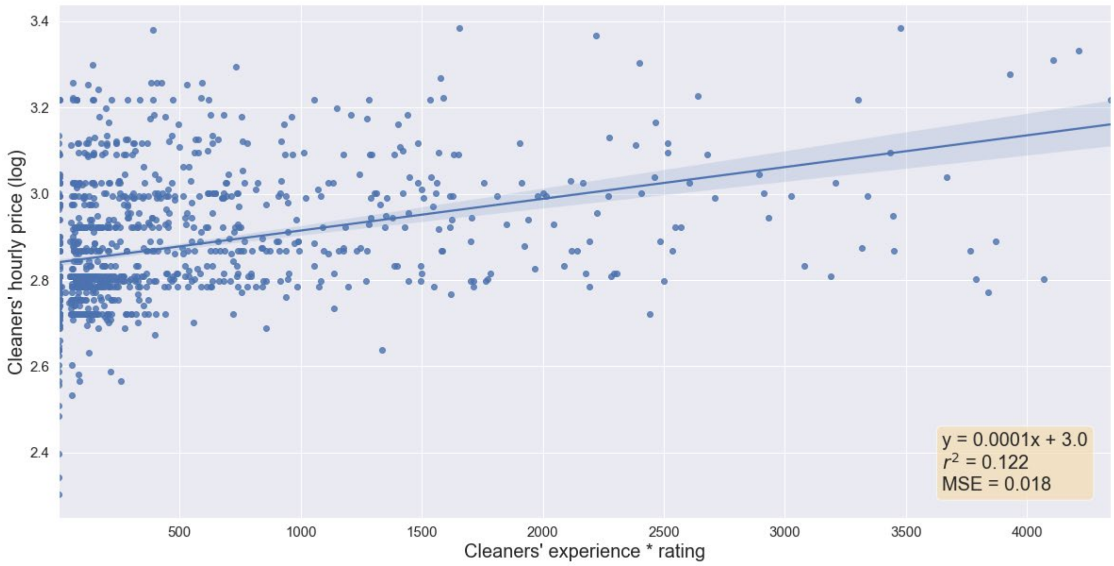
Figure 9. Cleaners' duration and price



As expected, higher duration on the platform seems related to higher price. Each successive category shows this relationship.

Corresponding with Hypothesis 4, I next create an interaction variable, rating times experience, and plot it against price.

Figure10. Cleaners' rating * experience and price

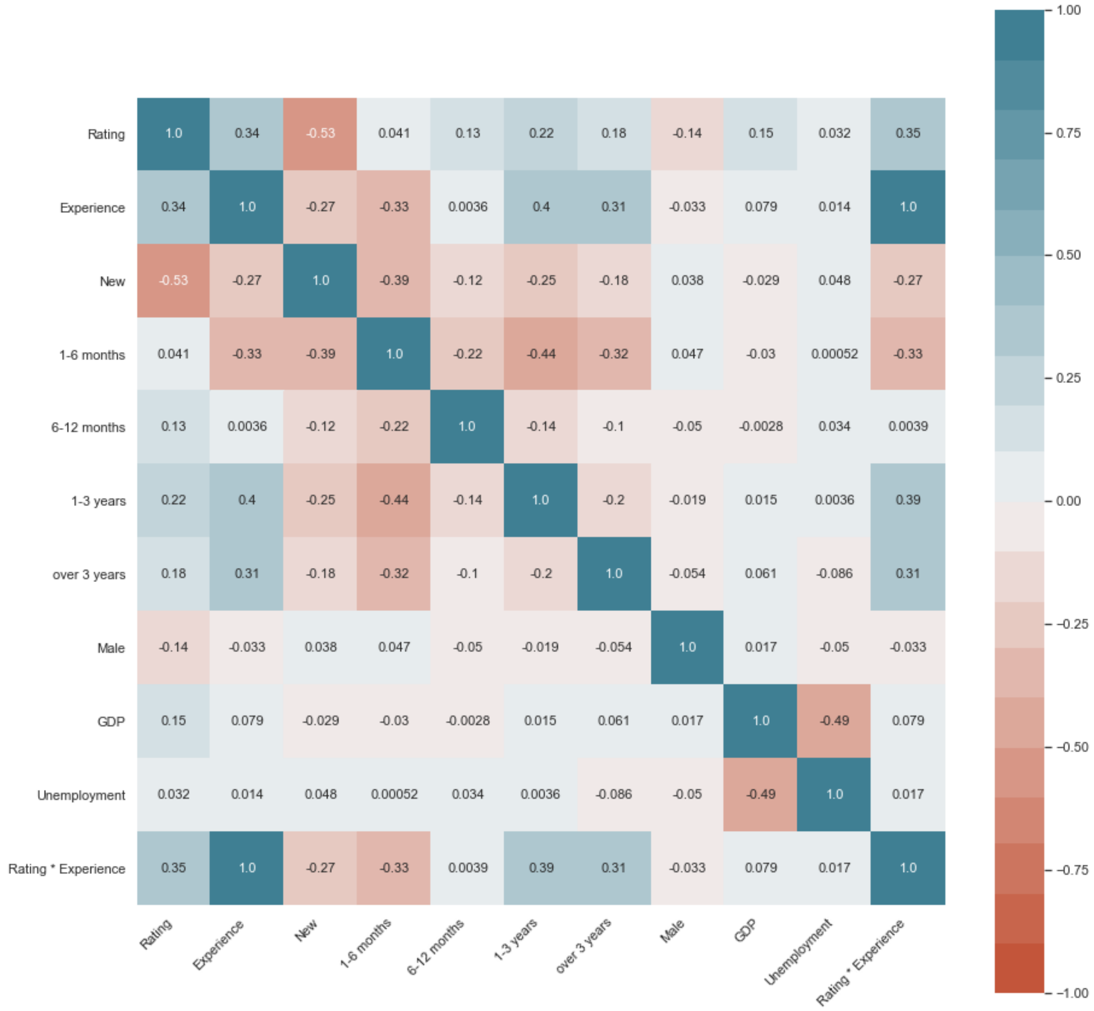


Note: The modified variables for rating and experience, as described above, were multiplied for this interaction variable.

It is not immediately clear if the interaction variable is much different than the experience variable alone, but this should become clearer in the regressions.

Next, I plot the independent and control variables against one another to understand their relationship. I suspect that experience and duration are quite closely related, as well as experience and the interaction variable of experience times rating. For the control variables, unemployment and GDP per capita may be very correlated as well. While I do not show all the variables for location (NUTS-3 region), these would also be very correlated with unemployment and GDP per capita.

Figure 11. Correlation matrix



Note: For the duration variable, each category was made into a Boolean.

A few of the variables are quite correlated. First, the 'New' cleaners have lower rating and experience. Correspondingly, the higher values of duration are correlated with higher experience, and to some extent, rating. Second, the control variables GDP per capita and unemployment are related, with higher GDP related to lower unemployment. Third, the interaction variable Rating * Experience is almost perfectly correlated with Experience. Upon further inspection, this seemed to be the case because there is very little variation in Rating (generally around 4.7), whereas Experience has a large range.

These results suggest that to avoid multicollinearity problems, models should not use location-based variables (Unemployment, GDP per capita, location) simultaneously, or use Experience and the interaction variable Rating * Experience simultaneously.

3.4.2 OLS

I next run linear regressions with ordinary least squares.[48] I use the data trimmed as described above, which reduces the number of observations from 1,420 to 1,338.

48 An additional option is quantile regression, which is sometimes used for pricing models.

The regressions proceed step-wise as outlined in Box 3, starting with independent variables alone, control variables alone, then each independent variable with control variables, before the final model, which is an attempt at best fit using selected independent and control variables.

Box 5: Regression model summaries

Independent variables alone

M1: log(Price) ~ Rating
M2: log(Price) ~ Experience
M3: log(Price) ~ Duration
M4: log(Price) ~ (Rating * experience interaction)

Control variables alone

M5: log(Price) ~ Gender (male)
M6: log(Price) ~ Unemployment
M7: log(Price) ~ GDP per capita
M8: log(Price) ~ NUTS-3

Independent and control variables

M9: log(Price) ~ Rating + Gender + Unemployment
M10: log(Price) ~ Experience + Gender + Unemployment
M11: log(Price) ~ Duration + Gender + Unemployment
M12: log(Price) ~ (Rating * experience interaction) + Gender + Unemployment
M13: log(Price) ~ Rating + Experience + Duration + Gender + Unemployment

4. Results

4.1 Models 1-4

Table 3. OLS regression results part 1

	Dependent variable: Cleaner price (log)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Rating	0.02251*** (0.00200)			
Experience		0.00039*** (0.00003)		
Rating*experience interaction				0.00007*** (0.00001)
Duration (1-6 months)			0.03746*** (0.01018)	
Duration (6-12 months)			0.07874*** (0.01648)	
Duration (1-3 years)			0.13129*** (0.01149)	
Duration (over 3 years)			0.14966*** (0.01315)	
Intercept	2.777*** (0.009)	2.841*** (0.004)	2.802*** (0.008)	2.841*** (0.004)
Observations	1,338	1,338	1,338	1,338
R^2	0.087	0.122	0.145	0.122
Adjusted R^2	0.086	0.121	0.143	0.121
Residual Std. Error	0.136	0.133	0.132	0.134
F Statistic	126.911***	185.871***	56.743***	184.945***

Note: *p<0.1; **p<0.05; ***p<0.01.
Five significant digits shown for coefficients, three significant digits shown elsewhere.

Models 1-4 mostly turned out as expected.

Model 1 shows that rating is positively and significantly correlated with price, though it is a rather weak predictor. Rating alone explains less than 9% of the variation in price, and moreover, an additional star rating (i.e. from 4 to 5) only results in a 2.25% rise in price. This is hardly impressive considering that almost all ratings fall between 4 and 5.

In Model 2, experience is positively and significantly correlated with price. However, quite a bit of experience is necessary to see meaningful results; every 100 additional cleanings results in about a 4% rise in hourly price. Experience also explains about 12% of the variation in price, making it a stronger predictor than rating.

In Model 3, all categories of duration are in relation to 'New'. As expected, each of them are significant, positive, and successively stronger. Compared to a new platform worker, one with 1 month of experience would earn 3.7% more hourly; after six months, 7.8% more; after one year, 13% more;

and those with over 3 years of experience earn about 15% more. Note that the difference between those with 1-3 years and over 3 years of experience is not nearly as large of a jump as with previous categories. The duration variables explain about 15% of the variance in price.

In Model 4,[49] the interaction term is positive and statistically significant, but like experience, very weak. An additional one star in rating, and an additional 100 cleanings, would result in a 4.5% higher hourly price. If rating were held constant, an additional 100 cleanings would result in a 3.1% higher price. While this does not intuitively seem like much, recall the way that the rating and experience variables were transformed. A person with no rating and no experience has had both values set to 1. As such, the model predicts that a person who performed just ten cleanings, and went from no rating to the median of 4.7, would have an hourly price 3.6% higher than someone just starting out. The interaction term therefore helps show that there is a price penalty associated with starting new as a platform worker. On the other hand, the adjusted R^2 for Model 4 is not better than that for Model 2 (experience alone). In short, the interaction term seems to have the predicted effect, but the impact is almost identical to experience alone. This may be due to the lack of variation in ratings.

4.2 Models 5-8

Table 4. OLS regression results part 2

	Dependent variable: Cleaner price (log)			
	Model 5	**Model 6**	**Model 7**	**Model 8**
Male	-0.035*** (0.008)			
Unemployment		-0.047*** (0.002)		
GDP per capita (EUR 1000s)			0.003*** (0.000)	
DE712				-0.188*** (0.032)
Intercept	2.891*** (0.006)	3.068*** (0.011)	2.710*** (0.010)	3.026*** (0.020)
Observations	1,338	1,338	1,338	1,338
R^2	0.014	0.219	0.186	0.436
Adjusted R^2	0.014	0.219	0.185	0.388
Residual Std. Error	0.141	0.126	0.129	0.111
F Statistic	19.513***	375.464***	304.534***	9.153***

Note: *p<0.1; **p<0.05; ***p<0.01
All figures shown to three significant digits.
DE712 is the first of the NUTS-3 regions, others shown in Appendix. See discussion below.

Models 5-8 show just the control variables.

Model 5 shows that gender is a significant indicator, but its predictive power is quite weak, explaining 1.4% of the variance in price. Unexpectedly, men earn around 3.5% less per hour than women.

49 Note that due to the high level of collinearity between Experience and the interaction term Rating * Experience, the effects on the dependent variable cannot be disentangled if run together in a regression. When running rating, experience, and the interaction variable together, the interaction variable loses its significance and the coefficient becomes slightly negative. Rating stays very significant but its coefficient weakens, while experience becomes slightly less significant, but its coefficient becomes much stronger. Interpreting these results is tricky, as the coefficient of individual variables would hold when the other variables have a value of 0, which cannot be the case in the data.

It may be that clients prefer to hire women to enter and clean their home, and therefore men offer slightly lower rates.

In Model 6, unemployment turns out to be quite a strong predictor. For areas with 1% higher unemployment, cleaners earn 4.7% less per hour. Unemployment explains about 22% of the variance in price, making it the best predictor so far.

Model 7 shows that GDP per capita also significantly and positively impacts price, explaining 18.5% of its variance. Cleaners in an area with 10,000 higher GDP per capita earn 3% more hourly. Given that GDP per capita in the data ranges from 20,000 to 180,000, this can make quite a large difference.

Model 8 shows the geographical location variable, NUTS-3 region. Because over 100 NUTS-3 regions are in the data, only one (DE712) is shown above, while the rest are in the Appendix. As shown in the Appendix, most locations prove to be significant determinants of hourly price. This is sensible for at least two reasons. First, wages and cost of living vary throughout Germany. For example, we would expect (and indeed observe)[50] that cleaners in Stuttgart charge more than average. Second, the amount of clients and platform workers in a given location impacts the supply and demand. If relatively few workers are available, and relatively many clients searching for services, then workers may have more margin with which to set their prices. The NUTS-3 regions explain a great deal of the variation in price - around 39% - making it the strongest predictor in the data.

All control variables prove to be significant. However, it is not possible to use unemployment and GDP per capita simultaneously (see discussion by Figure 11), and NUTS-3 regions (Model 8) add over one hundred variables to the model. To achieve the best and most parsimonious model, the next regressions will use only gender and unemployment as control variables.

50 Alphabetically, the first German NUTS-3 region (DE111) is central Stuttgart, which is the reference for other locations and not shown in the regression tables. Stuttgart recently surpassed Munich as the most expensive city in Germany. Almost all other regions show a negative and significant coefficient, meaning prices are significantly lower per hour than in Stuttgart.

4.3 Models 9-13

Table 5. OLS regression results part 3

	Dependent variable: Cleaner price (log)				
	Model 9	**Model 10**	**Model 11**	**Model 12**	**Model 13**
Rating	0.0226*** (0.0017)				0.0132*** (0.0020)
Experience		0.0004*** (0.0000)			0.0002*** (0.0000)
Duration (1-6 months)			0.0305*** (0.0088)		-0.0035 (0.0095)
Duration (6-12 months)			0.0759*** (0.0143)		0.0200 (0.0149)
Duration (1-3 years)			0.1231*** (0.0100)		0.0468*** (0.0118)
Duration (over 3 years)			0.1248*** (0.0115)		0.0455*** (0.0131)
Rating*experience interaction				0.0001*** (0.0000)	
Male	-0.0300*** (0.0066)	-0.0386*** (0.0064)	-0.0346*** (0.0064)	-0.0386*** (0.0064)	-0.0298*** (0.0062)
Unemployment	-0.0489*** (0.0023)	-0.0486*** (0.0022)	-0.0461*** (0.0022)	-0.0487*** (0.0022)	-0.0480*** (0.0021)
Intercept	2.999*** (0.013)	3.067*** (0.011)	3.023*** (0.013)	3.068*** (0.011)	3.002*** (0.013)
Observations	1,338	1,338	1,338		1,338
R^2	0.014	0.219	0.186		0.436
Adjusted R^2	0.014	0.219	0.185		0.388
Residual Std. Error	0.141	0.126	0.129		0.111
F Statistic	19.513***	375.464***	304.534***		9.153***

Note: *p<0.1; **p<0.05; ***p<0.01.
Four significant digits shown for coefficients, three significant digits shown for summary statistics.

Models 9-13 show the independent variables with control variables.

Model 9 is essentially identical to Model 1, showing that rating is a statistically significant, but rather economically insignificant, predictor of price. The control variables are more or less the same as when testing them independently.

Model 10 is a similar story, as experience and the control variables maintain the same relationship as previous regressions showed.

Model 11 is mostly the same as Model 3, except the coefficients are a bit weaker for 1-3 years and over 3 years. One interesting change is in the adjusted R^2. In Models 2 and 3, which had no control variables, duration was quite a bit better at explaining variance in price. After adding gender and unemployment, the models with experience and duration both explain around 36% of the variance in price.

Model 12, like Model 4, shows that the interaction term rating * experience is positively and significantly correlated with price. However, the coefficient became about 43% stronger (from 0.00007 to 0.0001). In this model, a person with a constant rating of 4.7, would see their hourly price rise 5.2% after an additional 100 cleanings. A person with experience of 105 and rating 4.9 would earn 5.4%

more than a person with rating of 4.4 and experience of 5. Again, rating is not very economically meaningful, unless you have no rating at all.

Finally, Model 13 shows the preferred regression with the most information, explaining 41% of the variance in price. Interestingly, the independent variables become a bit weaker when run together. An additional star rating now increases hourly price only 1.3%, and an additional 100 experience increases price by 2%. The story of experience could be more complicated than simply 'more experience, higher wages'. For example, platform workers in need of money may set lower prices to find work more quickly.

The first two categories of duration, 1-6 months and 6-12 months, lose their significance, and the longer durations, 1-3 years and over 3 years, only earn about 5% more than a baseline worker. This may indicate that price is best predicted by a mixture of multiple factors, which refines the story from Models 1-4, which made it seem like duration was a far better predictor than experience. Unemployment is virtually unchanged from previous models, while the coefficient of male stays about the same.

4.4 Summary

Models 1, 9, and 13 suggest that continuous rating is a statistically significant and positive determinant of price, though rating did not turn out to be a very economically significant indicator. Model 9 suggests that for each additional star rating, price increases 2.2%, where Model 13 shows an increase of 1.3%. This is hardly impressive, given the maximum star rating of 5, and that almost all cleaners fall around 4.7 to 4.8 stars. I nevertheless **accept the first hypothesis:** ***Higher average ratings are positively correlated with hourly price***.

Looking to cleaner experience, Models 2, 10, and 13 reveal a significant and positive correlation with price.[51] Model 8 shows that each additional 100 cleanings leads cleaners to request an additional 4% in hourly price. While Model 13 shows a weaker relationship – an additional 100 cleanings leads to an additional 2% in hourly price – the relationship stays otherwise the same. I therefore **accept the second hypothesis:** ***Higher experience is positively correlated with hourly price***.

In Models 3 and 11 for duration, the reference is those who have been on the platform for under one month. These models show that each successive category becomes more positive, while all are significant. Moreover, the effect of duration appears to be stronger than rating or experience. After one month on the platform, cleaners earn 3.5% more. Six months after starting, cleaners earn 7.5% more than their starting wage, and so on. While the predictive power of duration decreases in Model 13, it still shows the same general relationship with price. I therefore **accept the third hypothesis:** ***Longer duration on the platform is positively correlated with hourly price***.

Finally, we look to the interaction effect. Models 4 and 12 indeed show a significant and positive effect of rating * experience on price. This is grounds to accept the **fourth hypothesis:** ***The weight return to ratings increases with the number of tasks a platform worker has completed.*** However, I would note that it is unclear if the interaction effect of rating * experience performs better than experience alone.

51 In Model 5, where the interaction effect is added, the coefficient of experience is the unique effect of experience on price when rating = 0, which cannot exist. Thus, Model 5 does not provide evidence against Hypothesis 2.

5. Discussion

In this case study, I have presented a strategy to webscrape and analyse data from a labour platform. The analysis shows that the data mostly support the hypotheses; rating, experience, and duration are meaningful signals in platform marketplaces that demonstrably impact workers' earnings. The results illustrate the importance of ratings and evaluations in platform work, lending credence to the notion that **fair platform work requires close attention to rating and reputation systems**. This evidence is especially notable due to the limited flexibility cleaners have to set their prices. I expect rating is a stronger predictor for other types of platform work such as programming or consulting.

The results suggest that rating is a statistically significant, but economically insignificant, determinant of price. This may indicate that rating is more of a pass-fail mechanic, whereby clients will not hire a cleaner below a certain rating, but otherwise do not care very much. Alternatively, workers with low ratings may voluntarily drop out of the platform, or be removed, as in the case of Uber drivers.

A related idea that future researchers could explore is a longitudinal one; how likely are platform workers with low ratings to find future work, or drop off the platform? I suspect that the answer is quite a bit less likely to find work, and quite a bit more likely to drop off voluntarily or otherwise. Moreover, such effects may be more pronounced than that on price discussed in the present report. If so, it would further cement the notion that platform workers need transparency in rating and evaluation metrics, as well as the ability to contest unfair reviews.

I also note the importance of the region for price, as NUTS-3 region turns out to predict more of the variation in price than any other variables. Clearly areas with a higher cost of living would be expected to have higher labour costs. However, when reviewing the data and focusing on any specific NUTS-3 region, prices among platform workers are extremely similar. It may therefore be a sort of price collusion, where cleaners simply match their peers' prices and hope to be selected based on their availability or other factors.

It is also interesting that duration is such a strong indicator of price compared to ratings, at least when considered alone. In this particular type of platform work, one possibility is that maximising the quality of cleaning service is not the main priority of clients. Instead, they may simply want someone who can do a 'good enough' job of cleaning, while being trustworthy. Having a longer track record, rather than a stellar rating, may be more important in this respect. Alternatively, it could simply be that ratings are too inflated to be a good signal of quality.

On the other hand, it is rather strange to think that a cleaner who opened an account a year ago, then was inactive for a year, then began working suddenly, should merit a higher price. This is also interesting with regards to interface design. The platform determines which signals to show clients, and in the case of duration, even sets the value. Based on the results of this study, duration certainly seems to be a stronger indicator than clients' ratings, which are the only direct measure of service quality available.

While this case study does not focus on gender, it revealed an unexpected finding on this particular platform – on average, women earn 3% to 4% more than men. This result is very significant and consistent across all models. I propose two possibilities for the difference: first, clients generally see domestic work as women's work; and second, clients are less comfortable with inviting an unknown man into their home.[52] This may indicate that gender biases present in the general labour market

52 See, for example, van Walsum's research in the Netherlands: All of my informants agreed that Dutch employers generally saw domestic work as women's work and tended to prefer women (2011: p. 153).

persist in platform work, while not necessarily meaning that women's earnings always suffer as a result.

In conclusion, web-scraped data is a valuable tool to examine how labour platforms function, and investigate earnings for platform workers. It is also an interesting strategy to better understand the impacts of interface design. Researchers could further build on this line of inquiry by gathering longitudinal data on different platforms in different locations, and implementing more sophisticated tools than OLS. For example, Lasso (least absolute shrinkage and selection operator) may be more useful to sort out which variables best predict price, while improving prediction accuracy and enhancing interpretability (Brownlee, 2020). It would also be interesting to use machine learning techniques to analyse whether aliases/names or profile pictures impact prices. In this platform, for example, platform workers who look German or have a German-sounding name may earn more or less than their peers.

appendix 1

Table a1. OLS regression results part 2 (all regional variables)

	Dependent variable: Cleaner price (log)			
	Model 5	**Model 6**	**Model 7**	**Model 8**
Male	-0.035*** (0.008)			
Unemployment		-0.047*** (0.002)		
GDP per capita (EUR 1000s)			0.003*** (0.000)	
DE712				-0.188*** (0.032)
DE254				-0.004 (0.034)
DEA13				-0.157*** (0.030)
DE212				0.032 (0.022)
DE300				-0.240*** (0.021)
DE933				-0.104* (0.054)
DEA17				-0.138*** (0.032)
DE128				-0.133*** (0.050)
DE600				-0.130*** (0.023)
DEA23				-0.126*** (0.025)
DEB11				-0.087* (0.050)
DEA22				-0.105*** (0.027)
DEA11				-0.057** (0.028)
DEF0F DEG01				-0.179*** (0.036) -0.275*** (0.037)
DEF09				-0.118*** (0.039)
DEA52				-0.147*** (0.030)
DE731				-0.270*** (0.037)
DEF02				-0.246*** (0.033)
DEB12				-0.191*** (0.033)

	Dependent variable: Cleaner price (log)			
	Model 5	**Model 6**	**Model 7**	**Model 8**
DEC01				-0.226*** (0.067)
DEA55				-0.164 (0.113)
DEA1B				-0.217*** (0.047)
DEA1C				0.043 (0.081)
DEF0D				-0.112** (0.047)
DE711				-0.162*** (0.041)
DE941				-0.215*** (0.039)
DE713				-0.127*** (0.044)
DE408				-0.192*** (0.034)
DEA27				-0.124 (0.081)
DEB3J				-0.001 (0.081)
DE71A				-0.122*** (0.047)
DEA2D				-0.187*** (0.032)
DE71C				-0.045 (0.081)
DE272				-0.461*** (0.113)
DEB34				-0.104*** (0.036)
DEA15				-0.076 (0.081)
DEA1A				-0.160*** (0.044)
DE142				-0.098 (0.113)
DEB33				-0.059 (0.038)
DEA28				-0.026 (0.113)
DE115				-0.060 (0.081)
DE251				-0.217* (0.113)
DE939				-0.160** (0.081)
DEF0A				-0.241** (0.113)

	Dependent variable: Cleaner price (log)			
	Model 5	Model 6	Model 7	Model 8
DEA5A				-0.241*** (0.054)
DE24B				-0.241** (0.113)
DEA2B				-0.309*** (0.081)
DE724				-0.217*** (0.054)
DE252				-0.100* (0.059)
DEA45				-0.162** (0.081)
DE263				-0.270*** (0.050)
DEA36				-0.133*** (0.041)
DEA51				-0.139*** (0.050)
DEA32				-0.217* (0.113)
DE271				-0.241** (0.113)
DE232				-0.241*** (0.067)
DE131				-0.136*** (0.047)
DEB39				-0.241** (0.113)
DEG07				-0.241** (0.113)
DE40A				-0.263*** (0.067)
DE124				0.087 (0.113)
DEA54				-0.175*** (0.047)
DEA37				-0.058 (0.081)
DEA47				-0.218*** (0.050)
DE936				-0.305*** (0.113)
DEG06				-0.252*** (0.050)
DE242				-0.241*** (0.081)
DE26B				-0.243*** (0.050)
DEA26				-0.241*** (0.081)

	Dependent variable: Cleaner price (log)			
	Model 5	**Model 6**	**Model 7**	**Model 8**
DEG0F				-0.235*** (0.067)
DEG05				-0.241*** (0.081)
DE803				-0.241** (0.113)
DEF01				-0.259*** (0.054)
DEF08				-0.241** (0.113)
DE241				-0.241*** (0.081)
DE139				-0.241** (0.113)
DE717				-0.241** (0.113)
DE501				-0.305*** (0.113)
DE944				-0.273*** (0.081)
DEB31				-0.305*** (0.113)
DE114				-0.087 (0.113)
DE211				-0.241** (0.113)
DE734				-0.285** (0.113)
DE80J				-0.241** (0.113)
DE279				-0.241** (0.113)
DE943				-0.136* (0.081)
DE21N				-0.241** (0.113)
DE253				-0.051 (0.113)
DEA53				-0.217* (0.113)
DEB35				-0.188** (0.081)
DE913				-0.241** (0.113)
DE71E				-0.241** (0.113)
DE91C				-0.241** (0.113)
DE732				-0.241** (0.113)

	Dependent variable: Cleaner price (log)			
	Model 5	Model 6	Model 7	Model 8
DE127				-0.241**
				(0.113)
DE222				-0.241**
				(0.113)
DE403				-0.305***
				(0.113)
DEB3C				-0.305***
				(0.113)
DEA5B				-0.056
				(0.113)
DEA35				0.192**
				(0.081)
DE406				-0.211*
				(0.113)
DEB25				-0.103
				(0.113)
DE935				-0.217*
				(0.113)
Intercept	2.891***	3.068***	2.710***	3.026***
	(0.006)	(0.011)	(0.010)	(0.020)
Observations	1,338	1,338	1,338	1,338
R^2	0.014	0.219	0.186	0.436
Adjusted R^2	0.014	0.219	0.185	0.388
Residual Std. Error	0.141	0.126	0.129	0.111
F Statistic	19.513***	375.464***	304.534***	9.153***

Note: *p<0.1; **p<0.05; ***p<0.01.
All figures shown to three significant digits.

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InGRID-2
Integrating Research Infrastructure for European expertise on Inclusive Growth from data to policy

Referring to the increasingly challenging EU2020-ambitions of Inclusive Growth, the objectives of the InGRID-2 project are to advance the integration and innovation of distributed social sciences research infrastructures (RI) on 'poverty, living conditions and social policies' as well as on 'working conditions, vulnerability and labour policies'. InGRID-2 will extend transnational on-site and virtual access, organise mutual learning and discussions of innovations, and improve data services and facilities of comparative research. The focus areas are (a) integrated and harmonised data, (b) links between policy and practice, and (c) indicator-building tools.

Lead users are social scientist involved in comparative research to provide new evidence for European policy innovations. Key science actors and their stakeholders are coupled in the consortium to provide expert services to users of comparative research infrastructures by investing in collaborative efforts to better integrate microdata, identify new ways of collecting data, establish and improve harmonised classification tools, extend available policy databases, optimise statistical quality, and set-up micro-simulation environments and indicator-building tools as important means of valorisation. Helping scientists to enhance their expertise from data to policy is the advanced mission of InGRID-2. A new research portal will be the gateway to this European science infrastructure.

This project is supported by the European Union's Horizon 2020 research and innovation programme under Grant Agreement No 730998.

More detailed information is available on the website: www.inclusivegrowth.eu

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