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// ULRICH LAITENBERGER, STEFFEN VIETE, OLGA SLIVKO, MICHAEL KUMMER, KATHRIN BORCHERT, AND MATTHIAS HIRTH

Unemployment and Online Labor

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Evidence from Microtasking[*]

Ulrich Laitenberger[†], Steffen Viete[‡], Olga Slivko[§],
Michael E. Kummer[¶], Kathrin Borchert[‖], Matthias Hirth[**]

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Abstract

We analyze the relationship between unemployment and the supply of online labor for microtasking. Using detailed US data from a large microtasking platform between 2011 and 2015, we study the participation and the number of hours supplied by workers in the US. We find that more individuals registered on the platform and completed microtasks as the unemployment level in the commuting zone increased. This effect was strongest in regions with a high share of low-skill workers. Our analyses of the intensive margin, the wage elasticity, and the temporal work patterns suggest that the increased participation was likely motivated by an effort to substitute income. Our findings suggest that microtasking platforms appear to be an interesting online labor market for less educated workers. However, we also observe very low retention rates, indicative of a solely transient participation effect.

Keywords: Crowdworking; Online platform; Unemployment; Wage Elasticity.

JEL Classification Numbers: J21, D29, D80, H41, J60, L17.

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[†] i3, Télécom Paris, Institute Polytechnique Paris; CRED, Université Paris 2 - Pantheon-Assas, France; and ZEW Mannheim, Germany. *laitenberger@enst.fr*.

[‡] German Council of Economic Experts, *steffen.viete@svr-wirtschaft.de*

[§] Rotterdam School of Management, Erasmus University, The Netherlands, *slivko@rsm.nl*.

[¶] University of East Anglia, Georgia Institute of Technology & ZEW. *michael.kummer@econ.gatech.edu*.

[‖] University of Würzburg, Lehrstuhl für Informatik III. *kathrin.borchert@informatik.uni-wuerzburg.de*.

[**] Technical University of Ilmenau, *matthias.hirth@tu-ilmenau.de*.

1 INTRODUCTION

Online labor markets (OLM) offer the promise of mitigating persistent frictions in offline labor markets, such as skill mismatch, distance, and the cost of worker mobility. Online tools for coordination and communication displayed an impressive ability to overcome these frictions to sustain a wide range of economic activity during the COVID-19 pandemic, at least temporarily.[1] This demonstration of potential raises the question of whether OLM can contribute to overcoming the limitations of offline labor and to what extent.

In this paper, we analyze how unemployment affects the adoption of OLM for microtasks. Microtasks are small, well-defined jobs such as video screening, transcription, picture matching, and completing surveys (Stuart et al., 2017). Microtasking is also used to prepare training data for artificial intelligence and machine learning applications. The data preparation segment was valued at US $500 million in 2018 (Cognilytica, 2019). All these jobs can be performed online and require only very basic quantitative or reading skills. Firms usually submit large orders consisting of many microtasks, which typically take between several seconds and 20 minutes to complete.

Because of these defining characteristics, the OLM for microtasks is a highly relevant setting for studying the digitization of labor. Like all OLM, microtasking is not bound by any geographic restrictions and enables a supply of labor between a potentially global pool of employers and employees. Moreover, microtasking is characterized by high worker autonomy and low entry barriers for a large demographic group (Deng and Joshi, 2016). These features enable open and highly flexible access to work, which could be an attractive alternative for low-skilled workers in times of economic distress. Also, the small size and large number of the tasks and the fact that every action is observed facilitate a detailed analysis of workers' labor supply choices.

We use internal platform data from Microworkers.com, a large US-based online labor market for microtasks. We analyze how regional unemployment in the US affects the labor supply (registrations, engagement) on this platform. We use data of platform activity by US workers for the period 2011 to 2015 and combine them with data on unemployment from the Bureau of Labor Statistics.

[1] See, e.g., https://www.cnbc.com/2020/04/03/how-zoom-rose-to-the-top-during-the-coronavirus-pandemic.html or https://glginsights.com/articles/zoom-microsoft-teams-and-slack-have-exploded-due-to-the-covid-19-pandemic-can-they-hold-onto-this-growth/.

Our data are ideally suited to generating novel insights into the supply of online labor. Microtasks come in divisible batches which are handled by multiple workers, with wages set by employers. Compared to other forms of online labor (in which tasks are idiosyncratic and wages determined through a competitive bidding process), our setting facilitates the analysis of wage elasticities and reservation wages at different times of the day. Moreover, the services intermediated via microtasking platforms typically do not exist offline, which allows us to study a broader type of labor substitution. Workers who enter in this OLM have to engage in a new type of work and learn new skills. These are important differences from online freelancing, in which workers bid for unique and larger jobs (”gigs”) and which require existing skills and domain knowledge (e.g., as a language editor or programmer).

Despite these advantages of microtasking data, measuring a causal effect of unemployment on participation in OLM is not straightforward. Unobserved factors could drive both the unemployment rate and participation on the microtasking platform. Specifically, unobserved changes in the labor supply may be a concern that can bias estimates in both directions: If worsening local labor market conditions induced a migration of individuals who are more likely to engage in online work, then our estimates would be biased downward. If economic hardship resulted in a worsening internet infrastructure, which is needed to work online, then our estimates would be biased upward.

We address these challenges by exploiting variation in unemployment at the commuting zone level in a set of fixed-effects panel regressions that can account for time-invariant structural differences between the commuting zones (e.g., internet infrastructure) and for nationwide shocks affecting adoption. Moreover, we use Bartik-style instrumental variables (IV) to account for the endogeneity of local unemployment and changes in these variables. We use a structural labor supply model to measure wage elasticities. This approach creates a unified framework that relates local unemployment to both the number of participating users (extensive margin) and the amount of supplied labor (intensive margin). Finally, we conduct recently developed diagnostic tests for the validity of the Bartik Instruments (Goldsmith-Pinkham et al., 2020).

We document three main findings. First, higher unemployment at the commuting zone level causes more individuals to join the platform and complete tasks. A one percentage-point increase in the regional unemployment leads to a 11.4 percent increase in the number of newly registered users and a 9.6 percent increase in new active users on the OLM for microtasks. However, the increase in registrations is not accompanied by a significant increase in the number of active incumbent users. Second, when unemployment increases, more users register on the platform in commuting zones with a high share of people who are white, male, and middle-aged (45-64 years old), and from regions with a low share of college graduates. The latter finding suggests that microtasking is of interest to low-skilled workers. Third, at the intensive margin of online labor supply (which is the amount of labor provided by each individual worker) we find higher unemployment to coincide with increased microtasking activity, especially during normal working hours, suggesting a pattern of labor substitution. Moreover, the online labor supply becomes more elastic with an increase in the unemployment rate. Workers do not react very strongly to wage changes, but they are more sensitive to higher wages if the unemployment rate is high, consistent with low retention rates.

Overall, we make three contributions. First, by showing that regional unemployment influences the supply of labor on microtasking platforms, we contribute to a nascent line of research on offline factors that influence OLM. We extend existing work for high-skilled freelancing in the 'gig economy' (Huang et al., 2020) to highlight a connection between unemployment and online-offline substitution of labor in microtasking. Second, we provide the first analysis that documents the role of unemployment in the supply of *low-skilled* online labor (microtasking). Our findings suggest that microtasking is an attractive online option for low-skilled workers, and that, in the eyes of such workers, OLM could become an alternative opportunity in regions that offer few job opportunities. We thus document the role of OLM for the future of work across *all* educational backgrounds. Third, microtasks enable a detailed analysis of workers' supply choices, such as of when work is performed. We leverage this potential to study substitution across both time of day and across a wide range of tasks. Our framework allows us to study both the extensive margin (participation) and the intensive margin (engagement), and variation in the elasticity of substitution varies with the level of unemployment.

Following this introduction, Section 2 connects the paper to the related literature. Section 3 provides background on the microtasking platform under study (Microworkers.com). Section 4 discusses our data set and Section 5 outlines the empirical approach. We report our results in Section 6. Section 7 discusses implications, and Section 8 concludes.

2 RELATED LITERATURE

Our work relates to three broad streams of the literature. First, a large stream of the literature is interested in substitution patterns between economic activity online and offline in general, and in labor markets specifically. The second stream focuses on microtasking platforms as a form of online labor and the demographic characteristics of their users, which are often called crowdworkers. A third line of research investigates digital markets and economic inequality.

Substituting offline activity online A major stream of previous research addresses the relationship between offline and online channels and documents substitution patterns between them in retail prices and advertising (Forman et al., 2009; Brynjolfsson et al., 2009; Goldfarb and Tucker, 2011). More recent work examines interactions between online and offline channels particularly in retail (Balakrishnan et al., 2014; Gallino and Moreno, 2014; Wang and Goldfarb, 2017; Bell et al., 2018; Jing, 2018; Mehra et al., 2018; Cui et al., 2021), and in grocery shopping (Chintagunta et al., 2012), the news media (Seamans and Zhu, 2014; Xu et al., 2014), hotels and accommodations (Zervas et al., 2017), finance (Xue et al., 2011; Luo and Zhang, 2013; Agrawal et al., 2015a; Lin and Viswanathan, 2016), and even in hate crimes (Chan et al., 2016; Müller and Schwarz, 2020). Other research explores complementarities between the online sector and offline sectors (e.g. in the health care industry, Dranove et al. (2014)), and how the mobile internet affects online channels and substitution patterns (Ghose et al., 2013; Xu et al., 2017). Goldfarb and Tucker (2019) and Vial (2019) provide recent overviews of this literature. Few studies analyze the relationship between unemployment and participation in OLM. Clearly, microtasking OLM could be particularly attractive for those who are under- and unemployed. Whereas freelancing requires specific (domain) skills, and workers have to maintain appropriate skill levels (Kokkodis, 2021; Kokkodis and Ipeirotis, 2016), learning and acquiring new skills is a defining feature of (and motivating factor for) microtasking (Chandler and Kapelner, 2013; Chandler and Shapiro, 2016). Hence, because microtasks are divisible and require lower skills, the entry barriers to this segment of online markets are much lower (Kuek et al., 2015; Katz and Krueger, 2017). Using data from a survey on the microtasking platforms Amazon Mechanical Turk and Crowdflower, Berg (2015) shows that about one third of online workers were unemployed prior before they began to participate in online labor. Ipeirotis (2010) and Difallah et al. (2018) document similar shares of the previously unemployed among those providing labor for Amazon Mechanical Turk. Using checking account data, Farrell and

Greig (2016) highlight that people resort to OLM after experiencing negative income shocks. Perhaps most closely related to our work, Huang et al. (2020) analyze how unemployment affects the labor supply of freelancers. They document a connection between unemployment and participation in OLM for complex ”macrotasks,” such as software development. They find that participation increased by 21.8 per cent following a 1 per cent increase in unemployment.

We contribute to this stream by providing a comprehensive analysis of a vast and complete data set of workers in microtasking in the US. We conduct a causal analysis, in which we substantiate existing descriptive and survey-based evidence on whether unemployment drivers worker participation in microtasking. Furthermore, we expand the existing work on online freelancing (Huang et al., 2020) to include a different and perhaps more encompassing form of online labor. The substitution to online work in our paper is not based on a worker's offline background, as in freelancing, and occurs on a global labor market. Our findings are therefore novel, because they specifically document that OLM are of interest to the unemployed who have lower educational attainments and are competing with other workers all over the world.

Microtasking as a form of online labor A thriving stream of research has emerged to examine microtasking. An early line of research focused on the phenomenon and discussed the best practices in lab-type experiments on microtasking platforms (Paolacci et al., 2010; Horton et al., 2011; Berinsky et al., 2014; Chandler et al., 2014; Kuziemko et al., 2015; Chandler and Shapiro, 2016). This stream is closely related to work that investigates the characteristics of microtasking as a form of labor (Peer et al., 2014; Chandler et al., 2014). Subsequent research focuses on understanding the quality of the work (especially data) produced on microtasking platforms (Steelman et al., 2014; Rouse, 2015; Peer et al., 2017). Related work documents the role (and limitations) of reputation systems for ensuring high quality in the work submitted on such platforms (Peer et al., 2014; Filippas et al., 2018). Gadiraju et al. (2017) show that workers on the microtasking platform Crowdflower achieve a better accuracy and task performance when having access to performant equipment and broadband internet.

Earlier research studied what motivates users to work online, and several papers found monetary incentives to be the most important driving factor (Brabham, 2010; Horton and Chilton, 2010; Ipeirotis, 2010; Kaufmann et al., 2011; Teodoro et al., 2014). Other motivations included the high levels of autonomy, fairness, accountability and the possibility of making an impact (Deng and Joshi, 2016), entertainment and learning (Ipeirotis, 2010; Brabham, 2010;

Chandler and Kapelner, 2013; Schnitzer et al., 2015; Chandler and Shapiro, 2016; Kost et al., 2018; Keskinen et al., 2021). Several surveys are aimed at better understanding the demographic characteristics of users on online labor platforms (Ipeirotis, 2010; Ross et al., 2010; Martin et al., 2017), and what determines their longevity there (Rani and Furrer, 2019; Mourelatos et al., 2020; Jiang et al., 2021). Martin et al. (2017) conduct surveys on the platforms Amazon Mechanical Turk, Crowdee and Microworkers.com. They discuss the demographic distribution at Amazon Mechanical Turk, finding that the majority of workers are US residents (50%-60%). In line with other studies, they show that most crowdworkers are highly educated, with a college or advanced degree, and that online labor platforms tend to be dominated by males.

Our research contributes the novel finding that online labor markets attract not only young and educated workers, but also older and less educated workers, especially when unemployment increases. Women do not seem to be more attracted to microtasking in times of unemployment, as Huang et al. (2020) found with respect to freelancing. This is surprising, given the flexibility of microtasking, which has been argued as being more valuable for women than for men.

Digital markets and inequality Offline labor markets are characterized by persistent frictions. Distance and transaction costs are often important barriers to geographic mobility of labor (Niebuhr et al., 2012; Artuc et al., 2015). Although OLM help to mitigate the offline labor market frictions, they affect income distribution and inequality (Gefen and Carmel, 2008; Agrawal et al., 2015b). For example, the descriptive evidence by Agrawal et al. (2015b) shows that the online labor market oDesk is dominated by a North-South exchange, with the employers predominantly in high-income countries and the contractors mainly in low-income countries. Because of the superstar (long-tail) effects, OLM might benefit contractors with either vertically differentiated skills (i.e., high-quality performers) or horizontally differentiated skills (i.e., niche performers), or lower cost performers, while those with mediocre quality, common skills, and higher costs are disadvantaged (Agrawal et al., 2015b). This effect is amplified when the ratings do not reflect category-specific experience and workers cannot build category-specific reputation (Kokkodis and Ipeirotis, 2016).

We add to this stream of literature by highlighting that the effect of unemployment on participation in microtasking is strongest in areas with (1) higher shares of old and male population, (2) less ethnic diversity, and (3) lower shares of educated workers. Together, these findings show that microtasking is an attractive option for workers with disadvantaged backgrounds.

3 BACKGROUND: MICROTASKING PLATFORMS

Online Labor Platforms and Microtasking The defining feature of OLM is that the product of labor is delivered completely online (Horton, 2010). OLM disconnect workers from any geographical restriction and allow for transactions over long distances between a potentially global pool of employers and employees. The advent of OLM was marked by the platforms Elance in 1998 and oDesk in 2003. Aggregating information from the 10 most important platforms, Frei (2009) estimated that OLM had generated $700 million in worker earnings by 2009. Since then, dozens of platforms have emerged that cater to different types of clients, workers, and projects. Many of these platforms have grown heavily (Kässi and Lehdonvirta, 2018).

As an important part of this specialization, *microtasking* was popularized by Amazon's Mechanical Turk in 2005. Microtasking platforms are crowdsourcing work environments which *aggregate* hundreds or thousands of microtasks which are performed by multiple suppliers. (Kaganer et al., 2013). Microtasks are well-defined jobs which typically take between several seconds and 20 minutes and require only very basic quantitative or reading skills (Deng and Joshi, 2016). Typical examples are video screening, transcription, picture matching, and completing surveys (Stuart et al., 2017), which require only time, a computer, and a stable internet connection (Gadiraju et al., 2017). The low barriers, granularity, open access, and high levels of flexibility, and worker autonomy can be highly attractive for crowdworkers and bear the promise of a transformed work context (Deng and Joshi, 2016). At the same time, crowdworkers often work alone, with little social contact and security, so that this form of organization results in an interesting duality of empowerment and marginalization (Deng et al., 2016).

Employers submit microtasks in large batches. The platforms, which are continuously improving their services and adding new functionalities, allow firms to track the completion of tasks and submit payments via the platform. These services generate value, which has resulted in the steady growth of OLM platforms in terms of participants, transactions or the variety of available jobs. Among other uses, microtasking is used in human-subject research (such as surveys or experiments), where it has facilitated hundreds of papers that are published in top journals every year (Chandler and Shapiro, 2016). Microtasking is also needed to prepare training data sets for AI and machine learning, which amounted to US $500 million in 2018 (Cognilytica, 2019). It is hard to quantify total producer surplus or the value of the research facilitated through the platforms, but the World Bank estimated that microtasking generated between \$450 and \$900 million annually, with an overall employment of between 1.45 and 2.9 million workers by 2012 already (Rossotto et al., 2012).

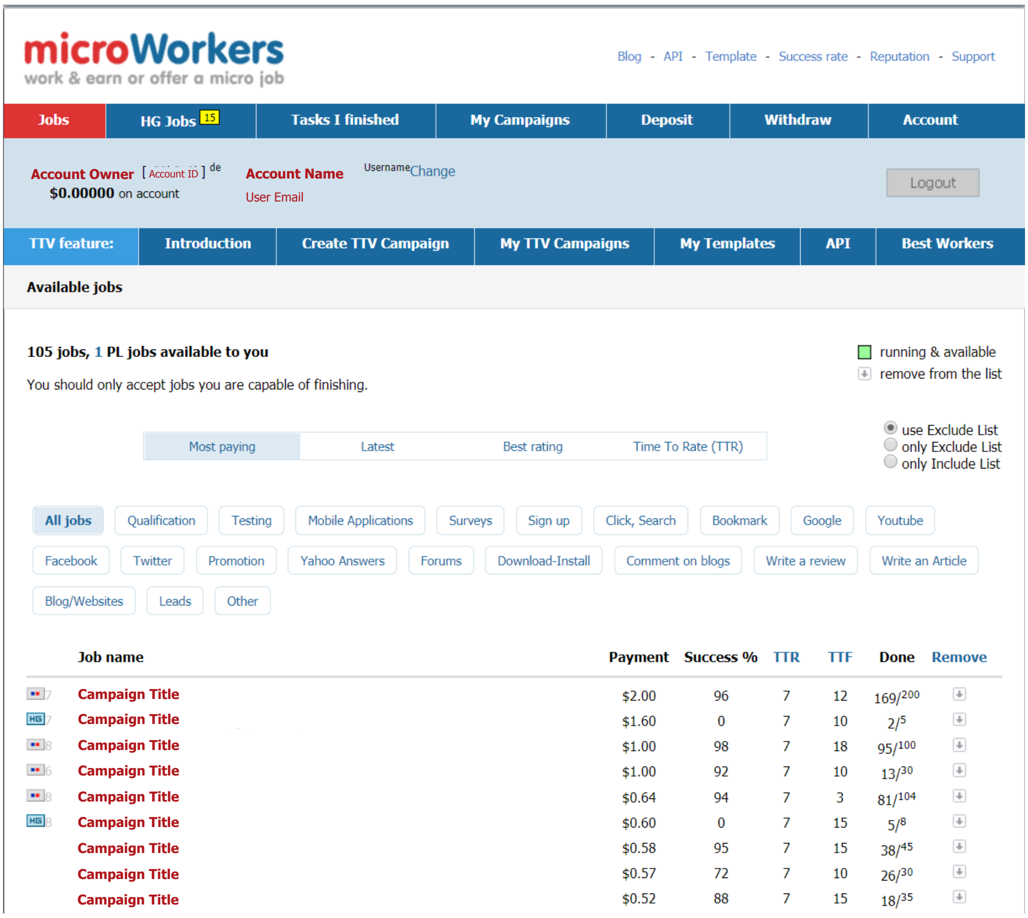
Microworkers.com Microworkers.com was launched in May 2009 and is a "classical" online platform for microtasks. By 2016, it had approximately 800,000 registered users who submitted over 261,000 campaigns and completed over 26 million tasks (Hirth, 2016). It has been considered as a relevant platform for studies by the International Labor Organisation (ILO) and the European Commission (Berg et al., 2018; Stuart et al., 2017).

Tasks on Microworkers.com are organized by jobs and campaigns with one campaign consisting of multiple jobs to be performed. When choosing workers for the task, employers can define eligible worker groups based on simple characteristics, such as country of origin or platform rating. Microworkers.com also has predefined job categories with different minimum payments depending on the complexity, time, and effort required. The individual jobs pay between \$0.10 and a few dollars. Types of tasks available on Microworkers.com range from very small and simple, such as video screening, transcription, picture matching, to software testing, surveys and slightly more complex tasks, such as writing articles or audio transcripts. Over time, the range of supported tasks has increased and more complex tasks have become available. Hirth et al. (2011) and Hirth (2016) provide a detailed description of the platform at the beginning of our period of study.

To become active on the platform individuals have to register, providing basic information, such as their name and email address. Once registered via a verified email address, individuals can view the marketplace and thus get information on the tasks that are available to them. In order to start working, individuals additionally have to verify their account with a phone number and a verification message. To match users to commuting zones we geo-located the IP addresses that are recorded in the data. In contrast to many other online labor platforms, users of Microworkers.com have only one login and can act as both worker and employer. Payments are conducted via online micro-payment services, thus no bank account in a specific country is required.

Figure 1 shows a screenshot of the marketplace for a newly registered user. For each task the user is provided with information on the payment, the success rate of previously performed tasks in the campaign, the share of tasks in the campaign already done, the estimated time it takes to finish the task (in minutes, based on employer information), and the time the employer needs to rate the work output of the employee. Once the task is completed, the employer can accept or reject the work output or demand a revision. In the case of acceptance, the employee gets paid. The reputation system rates employees according to their success rate, which is the relation of successful to non-successful tasks. To be able to continue performing tasks, employees have to keep their success rate above 75 percent.

Figure 1: Screenshot of the Microworkers.com Marketplace



NOTE: Account details and campaign titles anonymized.

Microworkers.com in comparison with other platforms Hirth et al. (2011) compare Microworkers.com to Amazon Mechanical Turk, showing that the crowdworkers are less US-centered on Microworkers.com than on Amazon Mechanical Turk. This conclusion is in line with contemporary and more recent analysis of the demographics of workers on Amazon Mechanical Turk (Ipeirotis, 2010; Difallah et al., 2018). Thus, working hours can be different on average. However, US residents make up one of the three biggest groups on Microworkers.com, and we solely focus on this subgroup of workers. Further differences relate to employers and hence the tasks demanded. Employers on Microworkers.com are less concentrated in the sense that 10 percent of employers account for 70 percent of the wage bill, compared to 90 percent of the wage bill on Amazon Mechanical Turk. Hirth et al. (2011) argue that this is due to Amazon Mechanical Turk being used more by mediators for other companies while on Microworkers.com employers are more often self-employed or use the platform for marketing purposes. Hence, creative tasks are slightly less present on Microworkers.com compared to Amazon Mechanical Turk. In a study commissioned by the International Labor Organization (Berg et al., 2018), a descriptive comparison between the platforms is conducted. They highlight that Microworker.com has a more international worker base in comparison to Amazon Mechanical Turk. A survey from 2017 found that Microworkers.com has a higher share of workers in Asia and the Pacific, Latin America and the Caribbean, and Africa compared to Amazon Mechanical Turk which is stronger in Northern America, Europe and Central Asia. The share of male US Amazon Mechanical Turkers is lower (52%) than overall on Microworkers.com (68%). Forty-four percent of US Amazon Mechanical Turk workers have a bachelor's or post-graduate degree, compared to 48 percent on Microworkers.com. They also found a higher incidence of American and Indian workers on Amazon Mechanical Turk and CrowdFlower who were dependent on crowdwork as their primary source of income compared to those on Microworkers.com. In our context, the presence of more workers from countries with a lower income could imply lower average reservation wages and a more competitive remuneration on Microworkers.com.

4 THE DATA

4.1 Data Set Creation

We combine information on platform activity with administrative data on US local labor markets. We use internal platform data from Microworkers.com on the activity of US workers between January 2011 and December 2015. We augment the data set with data on the local labor force and unemployment from the Local Area Unemployment Statistics (LAUS) by the Bureau of Labor Statistics (BLS). Furthermore, we use data on wages and employment by industry from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages

(QCEW). We complement this data with information on local demographics from the Annual County Resident Population Estimates by the US Census Bureau.[2]

We aggregate the data to commuting zones as defined by the US Department of Agriculture (Tolbert and Sizer, 1996; Autor et al., 2013).[3] Commuting zones represent clusters of counties with strong commuting ties. After merging the data from 709 potential commuting zones with our platform data, we obtain a sample of 657 local labor markets with 20 quarterly observations between January 2011 and December 2015. The final data set contains 13,140 commuting zone-quarter observations.

We use the commuting zone quarter level data for our baseline analyses at the extensive margin. To analyze the intensive margin, we expanded the data by another dimension, reflecting the complexity of tasks. We defined three categories on how much effort is needed to finish the task: low, medium, and high complexity.[4] Finally, for our analysis of time allocation in subsection 6.2, we added further information about the date and time of task completion.

4.2 Descriptive Statistics

Table 1 displays the descriptive statistics for the regressors and outcome variables used in the analysis. For reasons of confidentiality, all variables containing information on the platform (Panel A) are normalized by their maximum value across the commuting zone and time, and multiplied by 100 to increase readability. "New registrants" is the number of new users in a specific commuting zone and quarter, "Active users" are defined as those who perform at least one task in the relevant quarter. "Active users" are further distinguished by whether they had signed up in the current quarter ("new") or before ("old"). We have different measures for work volume transacted over the platform, which is i) the total number of "tasks," ii) the amount of "working hours" spent on these tasks (as indicated by the employer), and iii) the total "wage

[2] Local demographics data at the county level are only available on a yearly basis. Given that demographic characteristics have low variation over time, we linearly interpolate the yearly data in order to match them to our quarterly data.

[3] For the aggregation of county level data to commuting zones, we use the 2000 version of the crosswalk files provided by the US Department of Agriculture. We manually updated the crosswalk file to match regional identifiers in our administrative data up to the year 2016 using publicly available information from the US Census Bureau, the US Centers for Disease Control and Prevention and by David Dorn at `http://www.ddorn.net/data.htm`.

[4] We define low-complexity tasks as tasks which require few clicks and a short amount of time. These might include providing an email address, signing up for a newsletter, rating an image quality, or bookmarking a page. We assigned medium-complexity to tasks such as writing a short comment to blog post web pages. These tasks do not typically require more than 5 minutes. Finally, we assigned high-complexity to tasks that require more than 5 minutes time to complete and a certain level of creativity. Such tasks might include writing a post on a forum, making a video or audio transcription or translating a short document.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.
Panel A: Platform data (normalized × 100)				
New registrants	2.15	6.15	0.00	100.00
Active Users	2.06	5.92	0.00	100.00
Active Users (new)	1.71	4.92	0.00	100.00
Active Users (old)	1.56	4.87	0.00	100.00
Tasks	0.47	2.23	0.00	100.00
Working Hours	0.52	2.49	0.00	100.00
Wage sum	0.59	2.47	0.00	100.00
Panel B: Labor force data				
Population (M.)	0.39	0.78	0.01	8.70
Labor Force (M.)	0.24	0.60	0.00	9.04
Unemployment Rate	0.07	0.03	0.01	0.29
Offline wage in C.Z.	9.63	1.90	6.26	26.28
Panel C: Demographic data				
% age 15-24 (i)	0.24	0.03	0.15	0.45
% age 25-44 (i)	0.41	0.03	0.28	0.54
% age 45-64 (i)	0.35	0.04	0.23	0.51
% male (i)	0.50	0.02	0.46	0.59
% white (i)	0.84	0.14	0.11	0.99
% at least bachelor	0.21	0.07	0.07	0.51
% local FB friends	0.52	0.11	0.17	0.77
Observations	13140			

Note: This table shows the summary statistics for 20 quarterly observations of our main variables of interest for 657 commuting zones. The variables are organized in three groups: Panel A shows aggregate participation and activity of US residents on Microworkers.com. Active users performed at least one task in the respective quarter, and all indicators are normalized by the maximum value of each indicator respectively. Panel B gives labor force characteristics and Panel C demographic characteristics for the commuting zones in our data set. (i) indicates that data only available yearly and therefore linearly interpolated to the quarterly level.

sum." To measure how much users engage in tasks, we mainly make use of "working hours" as a fraction of disposable time.[5] In the analysis of labor supply at the intensive margin, we calculate the average hourly wage for three different complexity levels. Specifically, we divided the wage sum by the number of hours allocated to easy, medium, and difficult tasks respectively. The hourly wage for tasks of intermediate ("medium") complexity is 24.6% higher than for low complexity, and the hourly wage for "high" complexity tasks is 58.47% higher (not in table).

Due to differences in the size of commuting zones, the sample values for platform activity are highly skewed. Standard deviations for the measures of all users, registered users, and active users are higher than for the measures of volumes. Moreover, some commuting zones show no

[5] Working hours could be reported inaccurately by employers. However, our findings are qualitatively unaffected when measuring work volume by the number of tasks (cf. the Appendix C).

activity in some periods. We will consider periods with no activity only in the extensive margin analyses in subsection 6.1 but not in the intensive margin analyses in subsection 6.2.[6]

In addition to the variables that characterize platform activity, we add several control variables regarding labor force characteristics (Panel B) and population demographics (Panel C). The average commuting zone in our estimation sample has a population size of 387,512 and a labor force size of 236,755. The average unemployment rate in our sample is around 7 percent. The average quarterly wage per employee in the commuting zone (outside the platform) is US $9,634. We distinguish three age groups from 15 to 65 years, with the middle group aged between 25 and 44.[7] The average share of males is 50 percent, while on average share of white population is 84 percent. Following Huang et al. (2020), we add further information on the educational attainment measured by the share of individuals in the year 2012 that obtained a university or college degree (at least bachelor's), and we account for the dispersion of social connections by the share of Facebook friends that reside within a distance of 50km, as first proposed in Bailey et al. (2018).

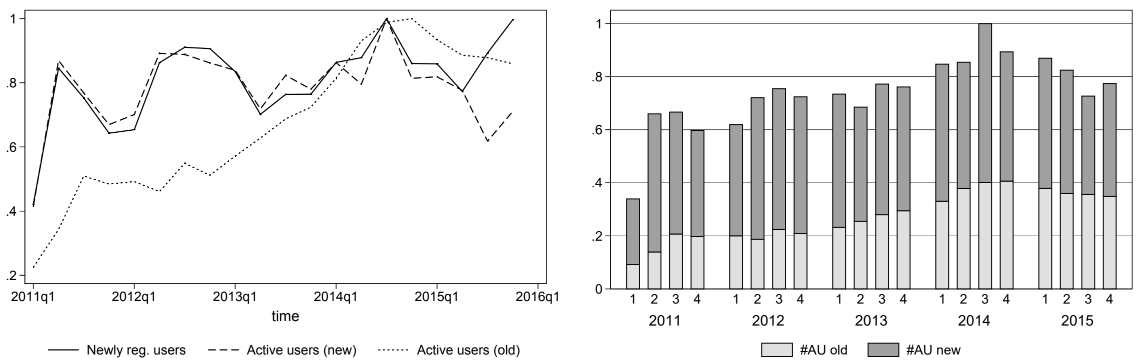
4.3 Activity on the Platform and Unemployment

To better understand the extent of variation in the data across commuting zones and over time, we report several figures on platform activity and unemployment. Figure 2 shows different measures for activities of US users on the platform from the beginning of 2011 to the end of 2015. The number of newly registered users and the number of new active users follow a similar pattern. This suggests that most users who register perform their first tasks in the same month. The right panel of Figure 2 indicates that the number of new and old active users was growing until 2014 but then saw a small decrease in 2015. Figure 3 shows the distribution of registered users over commuting zones. The map plots quintiles of the ratio of all registered users by labor force over our observation period. As expected, activity in the online labor market is concentrated on the east and the west coast of the US.

[6] The inclusion of zero activity commuting zones increases the statistical power of instruments and leaves the results qualitatively unchanged.

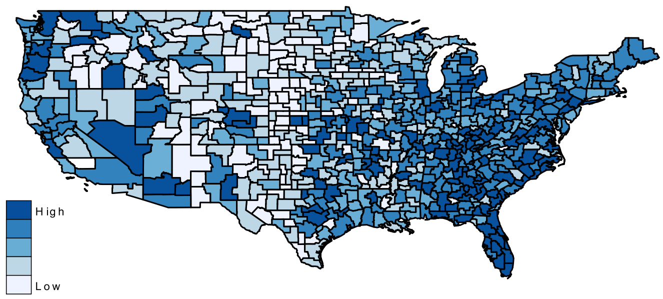
[7] Note that on Microworkers.com users have to be a minimum of 18 years old (See `https://www.microworkers.com/terms.php`). Nevertheless, we select the age groups in this way to be consistent with the unemployment data, leading to a potential slight downward bias in the estimated coefficient of the young group. We used the age group information from the total population as detailed labor force data was not available.

Figure 2: Aggregate Participation and Activity of US Residents on Microworkers.com.



NOTE: This figure displays the aggregate participation and activity of US residents on Microworkers.com. Active users are defined as users that performed at least one task in the respective quarter. All indicators are normalized by the maximum value of each indicator respectively.

Figure 3: Geographic Distribution of Registered User



NOTE: The map plots quintiles of the ratio of total registered users over the observation period and the size of the labor force in 2016. Dark regions belong to the highest quintile and light regions to the lowest.

5 METHODOLOGY AND IDENTIFICATION

5.1 Model

In our empirical application, workers take two decisions. First, they decide whether to register and work on the platform (extensive labor supply) and, second, they choose how much to work once they have registered (intensive labor supply). Generally, we cannot directly observe the choice *against* registering and working on the platform. Furthermore, our analysis is complicated by the fact that our data comes with individual choices being aggregated to commuting zones. We therefore apply methods from the discrete choice literature. Specifically, we reformulate a model of consumer demand originally developed by Berry (1994).

For using this methodology, we need to define a potential workforce and the maximum time that workers in a commuting zone could spend on the platform. Because of the low entry barriers to microtasking, we consider all members of the labor force in a commuting zone as potential workers, and assume that they may use all their available time to work on the platform.[8]

In the following, we first analyze the workers' choice of *whether* to register and become active on the platform (extensive margin). Subsequently, we use a second discrete choice model of labor supply to analyze *how much* work to perform (supply at the intensive margin).

Platform registration and participation (extensive margin) When deciding whether to register or to work at all on the platform, workers compare their expected utility of working on the platform with their outside options, such as working outside the platform. We define the potential microworker i's conditional indirect utility $u_{i,c,t}^{Entry}$ from joining the platform as

$$u_{i,c,t}^{Entry} = X_{c,t}\alpha + \beta UR_{c,t} + \xi_c + \xi_t + \epsilon_{i,c,t}, \tag{1}$$

where c is an index for the commuting zone the individual is living in, t denotes the time (here: quarter), $X_{i,c,t}$ are some time-varying commuting zone characteristics, $UR_{c,t}$ is the local unemployment rate, ξ_c is a commuting zone and ξ_t a time fixed effect, and $\epsilon_{i,c,t}$ are unobserved shocks that are independently and identically extreme value distributed.

Workers take these decisions with an expected platform wage in mind. This expected wage is constant for all users across commuting zones at a specific point in time and is absorbed by the time fixed effect ξ_t, so that we cannot include it explicitly. We closely follow the standard discrete-choice approach as outlined in Berry (1994) and sum up the workers' individual entry decisions to obtain aggregated choices at our level of observation. This approach results in a tractable linear estimation equation.[9] In our context, the dependent variable is the log of the "odds ratio" which divides the share of individuals joining the platform by the share of individuals that do not join. This ratio is estimated using the following specification:

$$ln({s_{c,t}}^{Entry}) - ln({s_{0;c,t}}^{Entry}) = X_{c,t}\alpha + \beta UR_{c,t} + \xi_c + \xi_t + \varepsilon_{c,t}, \tag{2}$$

where $s_{c,t}$ is the share of individuals in a commuting zone at one point in time that register on the platform, or perform at least one task in the quarter studied. $s_{0;c,t}$, in turn, is the

[8] An alternative approach would be using counts of registrants and task volumes in an ordinary least squares (OLS) approach. While this yields similar results (cf. corresponding results in Tables C1 to C3 in the appendix C), it does not account for fluctuations in the size of the population and different lengths of time periods, which can lead to measurement errors.

[9] For a detailed exposition and the mathematical derivation, see Berry (1994) equation (10) to (14).

share of individuals not choosing to do so. We estimate equation (2) for the number of newly registered and the number of active users, differentiated by newly active and incumbent users. We calculate the own-unemployment elasticity of online labor supply at the extensive margin, given by

$$\frac{UR_{c,t}}{s_{c,t}}\frac{\partial s_{c,t}}{\partial UR_{c,t}} = \eta_{UR} = \beta UR_{c,t}(1 - s_{c,t}). \tag{3}$$

This allows us to analyze how workers react to changes in the unemployment rate when taking their decisions.

Task performance by registered users (intensive margin) In the second step we model the decision of how many hours to work and which tasks to perform, once a worker has registered on the platform. Registered workers have time endowments and choose how much time to spend working on the platform. This choice depends on the disutility of doing potential tasks and on the compensation, which imply a *reservation wage*. The reservation wage is higher for less attractive or more demanding tasks, and for tasks that have to be completed at times of the day when workers have better outside options (see also Chen et al., 2017).

The two main factors that affect a user's reservation wage are their individual characteristics and a task's difficulty. For instance, unemployed individuals could have a lower reservation wage because of their lower alternative income possibilities. In contrast, they could also expect higher reservation wages if they are more skilled than the average incumbent worker. We assume that any registered user in a given commuting zone makes a decision on how to make use of each time unit (measured by minutes) per quarter. The compensation for completing tasks on the platform is set by the employers and microworkers are therefore wage-takers. We model the potential microworker i's conditional indirect utility from performing a task of type j at each point in time t again in a logit framework as

$$u_{i,j,t} = X_{j,t}\alpha + \beta w_{j,t} + \gamma w_{j,t} UR_{c,t} + \xi_c + \xi_t + \epsilon_{i,j,t}, \tag{4}$$

where the variable $w_{j,t}$ denotes the *global* wage per hour for task j which is set by the employer submitting task j at time t. $X_{j,t}$ contains observed task characteristics. ξ_c is a commuting zone and ξ_t is a time fixed effect. The vector α captures valuations by individuals for task characteristics, β is the marginal utility of the wage when the unemployment rate, $UR_{c,t}$, is at zero, γ measures the perceived additional utility of wage interacted with the unemployment rate. $\epsilon_{i,j,t}$ accounts for unobserved (by the econometrician) task and worker characteristics and is an i.i.d. extreme value distributed error term. The outside option captures other work opportunities online or offline as well as the option of not working at all. The outside option is normalized so that it has a mean conditional utility of zero: $u_{i_{0,t}} = \epsilon_{i_{0,t}}$.

As we have aggregate data, we only observe the share of time spent on the observed online labor market by all potential microworkers in commuting zone c for task j at time t, denoted as $s_{c,j,t}$. To achieve a linear specification, we apply (again) the inversion steps suggested by Berry (1994). This yields the following regression equation

$$ln(s_{c,j,t}) - ln(s_{c,0,t}) = X_{c,j}\alpha + \beta w_{j,t} + \gamma w_{j,t} UR_{c,t} + \xi_c + \xi_t + \varepsilon_{j,t}, \tag{5}$$

where $s_{c,j,t}$ is the share of hours spent by workers in commuting zone c at time t to conduct task j, and $s_{c,0,t}$ is the share of hours that is spent for other activities outside the platform.[10] Note that this equation does not include the unemployment rate as a standalone variable, since it is not task-specific.[11]

Without taking into account the unemployment rate, we expect β to have a positive sign, indicating that the remuneration contributes positively to the utility of performing the task. Additionally, if the unemployed are more reactive to wage changes on the platform, this should translate into γ having a positive sign.

After estimating the model, we calculate the own-wage elasticity of task supply by

$$\frac{w_{j,t}}{s_{c,j,t}} \frac{\partial s_{c,j,t}}{\partial w_{j,t}} = \eta_w = (\beta + \gamma UR_{c,t}) w_{j,t} (1 - s_{c,j,t}) \tag{6}$$

and then build the average over observations.

As we specify in more detail below, we obtain the data aggregated by task type, commuting zone, and quarter. Two additional layers – hour of the day and day of the week – are added later. We use this augmented data for robustness checks to show that unemployment affects platform activity mostly in the morning, when most people work.

[10] For simplicity, we assume that every worker has a time endowment of 24 hours per day, and can potentially also work every day in a quarter. The time not spent on doing tasks is then counted for the outside good.

[11] Variables that are not task-specific reflect a constant on workers' utility within a choice set; the coefficients in this model are only identified in their scale but not their level. Readers interested in the impact of including the unemployment rate as a standalone variable are referred to the Online Annex where we estimate reduced form models as well.

5.2 Endogeneity of unemployment as a threat to identification

The main threat to identification in our study are unobserved factors that could drive both the unemployment rate and participation on the microtasking platform. Such factors could be structural differences between the commuting zones, such as a less-developed internet infrastructure which both relates to a high unemployment rate but also limits participation online. As long as these factors vary little during the four years of our observation period, a potential omitted-variable bias can be mitigated by employing commuting zone fixed effects. Another concern could be nationwide shocks to the adoption process on the platform. Such shocks are captured by the most conservative definition of time fixed effects by year-quarter. Year-quarter fixed effects also mitigate a potential concern of variation in the competition from outside the United States. As long as variations in international competition on the platform affect all commuting zones equally, they act like a national shock, and are thus captured by the year-quarter fixed effects that we use in all specifications.

Endogeneity due to unobserved changes in labor supply. The largest remaining concern arises from potential endogeneity due to unobserved *changes* in the local labor supply.[12] Note first that endogeneity due to reverse causation is unlikely due to the minor relevance any single online labor platform - even Amazon's MTurk - played for the overall economy during the period under study.[13] A larger concerns arises if unobservable worker and infrastructure characteristics within a commuting zone might be correlated with both the unemployment rate and working online. To see the problem, consider the following example. If unemployment increases, younger individuals might move out of the commuting zone. If younger individuals are also more likely to engage in working online, we would underestimate the effect of unemployment on working online. Similar examples for other demographic and infrastructural characteristics can be constructed similarly.[14]

Use of Bartik instruments. We deal with this concern by an instrumental variable approach. We instrument the commuting-zone-level unemployment rate using a predicted commuting-zone-level unemployment rate, which combines national-level growth rates across

12 We do not expect local labor *demand* to be correlated with platform work, as the tasks mediated over Microworkers.com barely have a counterpart in "offline" employment.

13 Moreover, we verified with the platform owners that there was no regionally targeted advertisement, or any advertisement that targeted specific demographic groups, such as unemployed individuals.

14 An example for overestimating the effect of unemployment could arise if unemployment leads to a worse internet infrastructure (i.e. if unemployed people cannot afford access anymore). As internet infrastructure is needed to work online, we would overestimate the the effect of unemployment on working online.

industries with differences in the initial industrial structure across commuting zones. This instrument isolates a measure of local labor demand that is unrelated to local labor supply. It therefore allows us to separate demand-driven shocks to the unemployment rate from supply-driven shocks that could be correlated with unobservables that are simultaneously related to working online. This approach goes back to Bartik (1991) and has been used extensively in studies on local labor demand (Blanchard and Katz, 1992; Bound and Holzer, 2000; Autor and Duggan, 2003; Autor et al., 2013; Kroft and Notowidigdo, 2016; Adelino et al., 2017) or migration (Altonji and Card, 1991). Gould et al. (2002); Fougère et al. (2009) or Brown and De Cao (2017) use Bartik shocks to identify the causal effects of regional unemployment.

Construction of the instrument. Our instrument is a weighted average of the national-level unemployment rates across all industries defined at the 4-digit NAICS level (excluding own region employment). The weights are computed as the industry-specific fractions of the employed working-age population in a given commuting zone, and we calculate these weights in the year before the sample period ($t_0 = 2010$ in what follows). Formally, the local labor demand shock is constructed as

$$\pi_{ct} = \sum_{k=1}^{K} \gamma_{c,k,t_0} \left(\frac{E_{-c,k,t} - E_{-c,k,t-1}}{E_{-c,k,t-1}} \right) \tag{7}$$

where γ_{c,k,t_0} is the employment share of industry k in commuting zone c and base period t_0 and $E_{-c,k,t}$ is the respective national employment in period t excluding commuting zone c.

Identifying assumptions of the Bartik IV. The instrumental variable requires that national-level unemployment rates (excluding the focal commuting zone) are exogenous to commuting zone level worker characteristics in any individual commuting zone. This is plausible because commuting zones are small in size relative to the whole of the United States (there are 657 commuting zones in the US). Furthermore, the strategy also relies on the assumption that the industry structure is exogenous to the application. While the initial industry structure might be correlated with unobservable regional characteristics, our application of the Bartik instrument relies on the assumption that *conditional on observables,* the commuting zone-specific industry shares are exogenous to *changes* in the error term (cf. Goldsmith-Pinkham et al., 2020). We consider this assumption to be plausible in our context, because we rely on predetermined, time-invariant industry shares (based on 2010), and control for commuting zone fixed effects in all our models. Relevant changes in the error term would need to be related to microtasking (e.g. innovations to platform activity). However, such changes would only be a concern if they were simultaneously related to the industry structure.

In Appendix A we systematically explore the assumptions and validity of our Bartik approach. We compute Rotemberg weights and show a series of additional diagnostic tests suggested by Goldsmith-Pinkham et al. (2020). These checks also allow us to understand which industries drive the variation of our instrument.

Endogeneity concerns regarding platform wage. On Microworkers.com, employers largely set wages for the global (worldwide) market during our observation period.[15] Hence, we consider the effect of the single commuting zone on the equilibrium online wage on the platform to be negligible. Instead, as the labor supply to the platform within one commuting zone is small compared to the total (worldwide) labor supply on the platform, we assume that individuals within a commuting zone face a perfectly inelastic labor demand, such that the platform wage can be considered exogenous to our labor supply model. Similarly, employment trends in specific industries in the US are unlikely to have an effect on wages on the platform, because the share of US-American workers on the platform is simply too small.[16]

6 RESULTS

In what follows, we first study the extensive margin of online labor supply, which is the number of workers that join the platform and become active (subsection 6.1). After that, we turn to the intensive margin of labor supply which relates to the amount of time the average worker spends on the platform (subsection 6.2).

6.1 Registrations and Activity (Extensive Margin)

We estimate how unemployment affects the participation of workers on the platform using equation 2. We use our data on all commuting zones and quantify users' participation using new registrations and activity in commuting zone c and period t. We instrument unemployment using Bartik shocks to account for the endogeneity of the unemployment rate (cf. Section 5.2). We report the OLS results without correcting for this endogeneity in Table A1 in Appendix A.

15 At the end of our period of observation, the *Microworker.com* introduced a tool that allows employers to restrict workers from selected cities, but this change affects only 2 months of our data.

16 Even though US workers are the fourth-largest user group on Microworkers.com at the beginning of our observation period (Hirth et al., 2011), their share on all registered workers was only 11 percent, and it is plausible that they also do fewer tasks than workers from other top ranking countries.

Baseline results In Table 2 we show the baseline regression. The dependent variable measures the logged odds ratio of newly registered users (col. 1) and all active users on the platform (col. 2). Active users are further distinguished by whether they signed up in the current quarter (col. 3) or before (col. 4). We find a strong positive relationship between registrations and unemployment. Moreover, we also see a positive relationship between the number of active users and unemployment, which is only statistically significant for newly active users. These findings suggest that with an increase in unemployment, more users register and perform at least one task.[17] According to our estimates, a 1 percent increase in regional unemployment leads to a 0.8 percent increase in the number of newly registered users and a 0.67 percent increase of newly active users in the OLM.

The labor supply elasticity with respect to unemployment for low-skill microtasks are significantly smaller than those found in studies on skilled online labor. In particular, our estimation results correspond to a semi-elasticity for the number of users of 11.4. Thus for a one percentage point increase in the unemployment rate the number of registered users increases by 11.4 percent. This is nearly half the increase of the 21.8 percent that was found for high-skilled freelancing jobs (Huang et al., 2020).[18]

Comparison of OLS and IV results and diagnostics Before analyzing how these results vary across different demographic groups, we quickly comment on how the results of our Bartik IV compare to the OLS results reported in Table A1 in Appendix A. Accounting for the endogeneity of regional unemployment increases the magnitude of the labor supply elasticity with respect to unemployment compared to the OLS estimates. This is in line with our expectation as unemployment shocks tend to be larger in structurally weak regions with slower technology adoption. As workers from economically weaker regions with less robust employment are participating less, the OLS coefficients are biased toward zero.

As is recommended practice, we ran a series of diagnostic tests suggested by Goldsmith-Pinkham et al. (2020) to explore the plausibility of our Bartik instrument. Overall, the Bartik IV in our application behaves in the same way as in the "canonical setting" described in Goldsmith-

17 If we apply a wider definition of active users (at least three tasks per quarter), the number of active incumbent users also increases with unemployment. However, the more rigorous definition reduces the number of active users by a third. Results are available upon request.

18 Note, however, that our dependent variable is an odds-ratio while Huang et al. (2020) use a different specification with the log number of users. When estimating the same specification as they did, we arrive at a semi-elasticity of 9.6, which is even slightly smaller than in our main specification and thus less than half the one found by Huang et al. (2020).

Table 2: Results on the Extensive Margin, Instrumented with Bartik IVs

	(1) Reg. Users	(2) Active Users	(3) Active Users (New)	(4) Active Users (Old)
Unemployment Rate	11.385***	7.888	12.643**	8.440
	(3.993)	(6.475)	(6.199)	(6.019)
Offline wage	-0.048***	-0.016	-0.013	0.016
	(0.011)	(0.015)	(0.014)	(0.015)
% age 15-24 (i)	-7.150***	0.356	2.166	-3.064
	(1.820)	(3.166)	(2.923)	(3.860)
% age 45-64 (i)	1.933	5.448	3.317	12.107***
	(2.103)	(4.084)	(3.667)	(4.552)
% male (i)	-13.599**	-23.004	-24.047	-31.245**
	(6.515)	(15.336)	(14.716)	(15.488)
% white (i)	9.264***	-10.303*	-7.397	-20.375***
	(3.381)	(6.191)	(5.797)	(6.671)
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
Observations	13140	10945	10945	10945
Kleibergen-Paap Stat	27.02	18.05	18.05	18.05
UR elasticity	0.80	0.40	0.67	0.46

NOTE: The dependent variable measures the logged odds-ratio of newly registered users (col. 1), all active users on the platform (col. 2). Columns (3) and (4) distinguish active users which have registered in the same quarter ("new") and those who already signed up before ("old"). All regressions are two-stage least squares fixed effects regressions. First-stage results are provided in Table A1, OLS results are in Table A1. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Pinkham et al. (2020). Specifically, the explanatory contribution of industries to the variation in our instrument (measured by Rotemberg Weights) is very heterogeneous (see Table A2). The top five industries are "Support activities for mining, and oil and gas extraction" (2131), "Fruit and Tree Nut Farming" (1113), "Seafood Product Preparation and Packaging" (3117) and "Garment Pressing, and Agents for Laundries and Drycleaners" (7212) and "Federal and Federally-Sponsored Credit Agencies" (6111). They contribute more than half of the positive weights. All of these industries feature de-synchronized business cycles and are dominated by occupations for which no high formal qualification is required. This is consistent with our finding that registrations increase especially where the population has a lower educational attainment, as we will discuss in the next paragraph. Moreover, we find that structural differences across regions strongly explain unemployment trends, but less so national trends. This result underlines that our instrument is suitable for measuring the impact of regional unemployment. Finally, an overidentification test using national industry growth rates multiplied by local shares as instruments rejects the H0, which is likely the result of heterogeneity in how likely it is that workers from different industries will substitute into microtasking. All of these results are in line with the "canonical" example application in Goldsmith-Pinkham et al. (2020). We present these results in Appendix A.

Table 3: Results Newly Registered Users, Instrumented with Bartik IVs

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	11.385***	9.474**	11.004***	11.235***	11.703***	9.770**
	(3.993)	(4.520)	(4.140)	(4.033)	(4.021)	(4.065)
Offline wage	-0.048***	-0.053***	-0.037***	-0.045***	-0.049***	-0.048***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
% age 15-24 (i)	-7.150***	-6.808**	-6.919***	-5.492***	-6.383***	-7.841***
	(1.820)	(3.295)	(1.754)	(1.929)	(1.887)	(1.754)
% age 45-64 (i)	1.933	-2.181	-0.861	3.051	1.858	-1.479
	(2.103)	(2.712)	(2.129)	(2.112)	(2.178)	(2.329)
% male (i)	-13.599**	-11.200*	-30.649***	-10.074	-11.399*	-15.994**
	(6.515)	(6.245)	(7.713)	(6.653)	(6.570)	(6.567)
% white (i)	9.264***	10.850***	7.761**	8.441**	13.442***	6.406*
	(3.381)	(3.471)	(3.340)	(3.426)	(3.921)	(3.429)
%UR * % age 15-24		23.336				
		(32.235)				
%UR * % age 45-64		63.505***				
		(24.536)				
%UR * % male			250.117***			
			(65.734)			
%UR * % white				12.494**		
				(5.181)		
%UR * % education					-28.206***	
					(8.745)	
%UR * % local FB friends						-21.680***
						(6.792)
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13140	13140	13140	13140	13140	13100
Kleibergen-Paap Stat	27.02	7.07	12.62	13.95	14.82	15.62
Anderson-Rubin p-val.	0.00	0.00	0.00	0.00	0.00	0.00

NOTE: This table analyzes how the effect of unemployment on platform participation varies by demographic group. It replicates column 1 of Table 2, and then adds population shares of various demographic groups. The dependent variable measures the logged odds-ratio of newly registered users. All regressions are two-stage least squares fixed effects regressions. Regional unemployment is instrumented with Bartik instruments. A log-log specification is shown in Table C2. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Moderating effects in the extensive margin In Table 3 we analyze how the effect of unemployment on platform participation varies for different demographic groups. Column (1) replicates the results from Table 2. In column (2) we interacted the unemployment rate with the age profile of the population (share of individuals aged 15-24 years, 45-64 years).[19] Column (3) shows the interaction with the share of males, and column (4) adds an interaction with the share of white individuals in the population. In column (5) we build the interaction between the unemployment rate and the share of university degree holders and in column (6) we interact unemployment with the average percentage of local Facebook friends in the commuting zone.[20]

[19] Note that limited data availability forced us to interact unemployment with linearly interpolated, yearly regional demographics data.

[20] Adding all variables and interactions in a single model gives qualitatively similar results, but multicollinearity reduces the precision in the estimates.

Compared to the reference age group of 25 to 44-year-old workers, the relationship between regional unemployment and registrations is significantly stronger in commuting zones with a larger share of 45 to 64-year-old workers. There is no significant difference compared to the base group for for the 15-24 bracket. Furthermore, the relationship is stronger in regions with a higher share of male and white population. Importantly, the relationship between unemployment and platform sign-ups is stronger in commuting zones with a lower share of university graduates. These results highlight an important difference to prior studies on the demographics of the users on microtasking platforms like Ipeirotis (2010) and on the relationship between unemployment and *high-skill* online labor markets (Huang et al., 2020). These studies found that OLM primarily attract a young and educated user base, whereas we highlight that users from less privileged backgrounds are also attracted to microtasking when faced with higher unemployment rates. Finally, consistent with the finding of Huang et al. (2020), a higher share of local Facebook friends makes the adoption of OLM less likely, which is consistent with an interpretation according to which having many local contacts helps with finding local work opportunities and hence decreases the attractiveness of microtasking.

6.2 Activity at the intensive margin

We now turn to analyzing how regional unemployment affects the amount of time that users devote to working on the platform. We estimate the model described in equation (5) using data that distinguishes the work volume by the level of task complexity. Thus a unit of observation in this analysis is the volume of time dedicated to tasks of a certain complexity ℓ (high, medium, and low) that were taken up in commuting-zone c in year-quarter t. The dependent variable is the log of the odds ratio which uses the number of hours spent in commuting zone c on tasks of complexity level ℓ in period t as numerator. This quantity is divided by the hours that workers spent doing other activities not on the platform. All regressions include commuting zone and year-quarter fixed effects, as well as the complexity-specific national average wage per hour for work on the platform ("platform wage") and indicators for the task complexity level (with the omitted category being easy tasks). Commuting zone unemployment should only have a minor effect on the national platform wage, therefore we treat it as exogenous.[21]

[21] In Appendix C we provide an IV estimation which accounts for wage endogeneity using the local platform wage (at the commuting zone level) as explanatory variable, and instrument it with achieved wages in other commuting zones.

Baseline results and wage elasticities In column (1) of Table 4, we estimate the model using OLS. All coefficients in Table 4 conform to our expectations. Greater compensation affects the utility of performing a task positively, while disutility increases with the complexity of tasks. Applying equation (6) to back out the wage elasticity of labor supply, we find a moderate average wage elasticity of 0.15. This is in line with prior literature which finds a lower elasticity for the supply of online labor (Horton and Chilton, 2010; Dube et al., 2018, 2020) than for offline employment.[22] In column (2) we interact the platform wage with the regional unemployment rate. The interaction yields a positive coefficient, implying a higher marginal utility of compensation in areas with higher unemployment. Users are thus willing to work more for the same wage when unemployment increases, which is in line with the fact that their opportunity cost is lower when being unemployed. In column (3) we instrument regional unemployment with Bartik shocks. We observe that using the instrument increases the coefficient of the interaction term of platform compensation and the unemployment rate.

In line with expectations, labor supply in online labor becomes more elastic after an increase in the regional unemployment rate. We observe a higher valuation of wages (higher labor supply elasticity) when the unemployment rate is high. Moreover, while the average wage elasticity is negative when we instrument unemployment, it is positive in the areas with higher unemployment rates. Specifically, we computed the elasticities for several intervals and found that it is positive (and increasing) for commuting zones with unemployment rates higher than 6.5 percent.

Strength of the instrument in the intensive margin analysis Weak instruments can be a problem as standard asymptotic distribution theory may begin to break down, implying too small standard errors (Rossi, 2014). We note that the Kleibergen-Paap statistic is low. This is due to the omission of commuting zones without activity. When including commuting zones in the estimation sample without activity, we observe that the resulting coefficients lie between the specifications in columns (2) and (3), and the instrument yields a considerably higher first-stage F-statistic.[23]

[22] E.g. Camerer et al. (1997); Farber (2005, 2008, 2015); Fehr and Goette (2007); Crawford and Meng (2011).

[23] Following the discussion by Angrist and Pischke (2009; 2008), weak instruments in just-identified models are not a major concern as long as the first-stage coefficient differs from zero. They should be reflected in higher standard errors in the second-stage rather than seriously biased coefficients of interest. Nevertheless, in order to account for the low first-stage F-statistic, we also report the p-value for the Anderson-Rubin test. For applied examples using Anderson-Rubin tests for weak-instrument robust inference see Nunn and Qian (2014) or Asatryan et al. (2017). The very low p-value increases our trust in the instrument. Furthermore,

Table 4: Results on the Intensive Margin Labor Supply

	OLS	OLS	IV	
			First	Second
	(1)	(2)	(3)	(4)
Platform wage	0.016***	-0.013	0.089***	-0.245**
	(0.004)	(0.014)	(0.002)	(0.104)
Medium task complexity	-1.416***	-1.403***	-0.036***	-1.301***
	(0.038)	(0.039)	(0.002)	(0.058)
High task complexity	-2.406***	-2.399***	-0.018***	-2.344***
	(0.069)	(0.069)	(0.003)	(0.073)
Unemployment X Wage		0.320**		2.873**
		(0.140)		(1.147)
Bartik Shock X Wage			-0.051***	
			(0.016)	
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
Observations	16416	16416	16416	16416
Adjusted R^2	0.32	0.32		0.25
Model	fe	fe	fe	iv
Kleibergen-Paap rk LM statistics				9.25
Kleibergen-Paap Stat				9.94
Cragg-Donald Wald F				140.00
Anderson-Rubin p-val.			0.00	
Wage Elasticity	0.16	0.11		-0.26
at UR < 5%		0.00		-0.99
at 5% <= UR < 10%		0.10		-0.31
at 10% <= UR < 20%		0.32		1.14
at UR >= 20%		0.62		4.39

Note: The dependent variable measures the logged odds-ratio of working hours on Microworkers.com. Columns (1) and (2) are OLS fixed effects regressions and column (4) is estimated by two-stage least squares fixed effects. The respective first-stage results are provided in column (3). Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Effect heterogeneity across hours of the day Although our analysis confirms that platform activity increases with a rise in regional unemployment, the question remains whether online labor acts primarily as a complement or a substitute to traditional offline labor in times of regional economic downturns.

We therefore study how the activity of workers changes with increased unemployment across the hours of the day. If the effects we measure are driven by unemployed workers who substitute online labor for offline work, we expect to see larger effects of regional unemployment on online labor supply during regular working hours.[24] We augment our data set with two additional variables: the weekday and hour of the day, as measured in the time zone of the worker. We

the Cragg–Donald Wald F statistic (140.00) is well above the most stringent critical Stock-Yogo critical value suggested (Stock and Yogo, 2005).

[24] We recognize that this logic applies to the extent that access to online microtasking is restricted for workers at work. This would not hold true only if employed individuals experience a considerable drop in time constraints on the job during economic downturns.

then run a regression with the logged number of tasks as dependent variable and explain it by indicators of the hour of the day, as well as interactions with the unemployment rate.

We graphically illustrate the regression results from Table B1 (Appendix B) in Figure 4. Panel B contrasts the share of regular (offline) employees' working times according to American Time Use Survey (ATUS) with the temporal distribution of the tasks performed on Microworkers.com. While more than 60 percent of the regular employees work by 9am in the ATUS data, the activity on Microworkers.com peaks in the afternoon and continues until after midnight. Panel A visualizes the point estimates for the interaction terms of the hour of the day and the unemployment rate (for week days). The graph highlights that the strong positive effects of unemployment on the online labor supply occur between 7 and 11am. This corresponds to the time of the day when the majority of individuals start their regular offline job according to the ATUS.

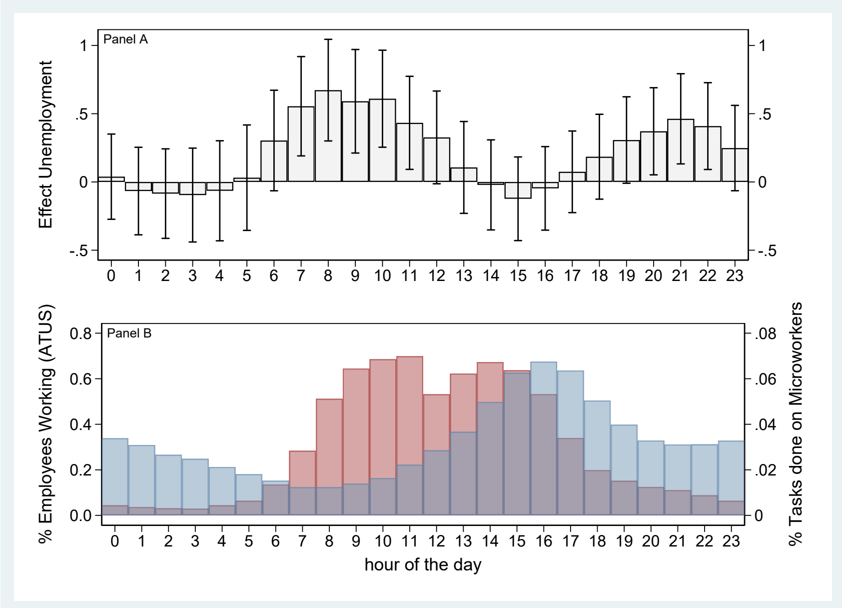
The results for the labor supply model accounting for hours of the day are shown in Table B3. The estimates indicate that workers have a lower valuation for wages when working during nights, after midnight, and on weekends (col. 1). In column (2) we add interactions of the unemployment rate with wage and hour of the day indicators to the model, in order to investigate the time of day at which the effect of unemployment is strongest. The results show that users have an increased valuation for wages in the OLM outside regular working hours, between 7-12 and 20-0 when the unemployment rate increases. We find that this effect occurs on weekdays (col. 3) rather than on weekends (col. 4).

Rather than acting as a mere complement to offline income, when unemployment rises individuals substitute online labor for tasks they would typically perform during regular working hours. In Figure B1 in Appendix B we additionally calculate the profile of labor supply elasticities over the day and conditional on the local unemployment rate, as implied by our estimation results.

6.3 Robustness Checks

In the previous section we showed that higher regional unemployment results in (1) increased numbers of registrations from the region, (2) a greater number of users who become engaged in online tasks, and (3) more elastic labor supply at the intensive margin. Following up on these results, we discuss the robustness of our findings in four ways. First, we employ a different

Figure 4: Effect of Unemployment on Labor Supply by Hour of the Day



NOTE: Panel A: Effect of the unemployment rate on the logged number of tasks by the hour of the day during weekdays (see Table B1 in Appendix B). Panel B: Share of employees working according to American Time Use Survey (ATUS) (red) and distribution of tasks performed on Microworkers.com (blue). Over half the population is working by 8am (ATUS). Most activity on Microworkers.com is from after noon to midnight.

empirical specification, second, we allow for the endogeneity of platform wages, third, we use different measures for labor supply, and fourth, we restrict our sample to commuting zones that do not span across any state borders.

Specification The modeling structure in our estimations is based on knowing the number of all eligible workers who could participate on the platform, which allows us to compute the shares of registered or active users (in analogy to a market share). While this structure provides us with a micro-foundation for our estimation approach, the requirement of knowing the number of workers introduces potential measurement error. To see whether our results are sensitive to our specification we estimated a log-log specification. Tables C1 through C3 in Appendix C show these results and show that our structural estimation results are very similar to regressions where the respective dependent variable and the unemployment rate are entered in logs. All results are qualitatively reproducible when we use this alternative parametrization of our main variables of interest.

Exogeneity of platform wage In our analysis of the intensive margin, we use the global platform wage for each task category as an explanatory variable. As explained above, we hold platform wage to be exogenous to the choices of the workers in any US commuting zone, given that the share of workers from the US is only 11 percent. In a robustness analysis in Appendix C we use the realized commuting zone-specific average wage and an instrumental variable instead of the global platform wage. As reflected in the negative wage coefficient in column (1) of Table 4, the locally realized wages are more prone to endogeneity issues, since users within the commuting zone self-select into performing certain tasks. Task preferences within a commuting zone might change when unemployment rises, due to changes in the average reservation wage. To account for this potential endogeneity problem, we therefore use the average wage in the category achieved in other commuting zones as an instrument. It varies in the willingness-to-pay of employers which acts worldwide while it is unaffected by changes in the local reservation wages due to deteriorating local economic conditions offline. After instrumenting, results are comparable to Table 4.

Alternative measure for work volume In the estimations for the intensive margin of labor supply we quantified labor by the time needed to complete a task, as reported by the employer. Although we are confident that employers have strong incentives to correctly estimate task duration, the estimate might introduce additional noise to our estimation. We therefore use the raw number of tasks completed on Microworkers.com as an alternative measure for labor supply. Specifically, we replicate the regression analyses of Table 4 in Table C5.[25] We find that our main findings remain qualitatively unchanged.

Heterogeneity in commuting zones spanning over multiple states In our data, we aggregate platform activity to commuting zones which partially span over several states.[26] This aggregation might be problematic if there is heterogeneity in state-specific developments, which might reduce the precision of our estimates. For instance, the great recession triggered unprecedented increases in the duration of unemployment benefits which phased out in 2013, when national funding was reduced (Hagedorn et al., 2013), leading to heterogeneity inside commuting zones that span across multiple states. We therefore run the estimations of Table 2 only for commuting zones that lie within one state. The results can be found in Table C6 in Appendix C and imply nearly the same elasticities as when using the full sample.

[25] Note that we do not apply here the logged odds ratio as in Table 4, as calculating the potential number of tasks that could be done in that period is not straightforward.

[26] Around 82 percent (582 out of 709) of all commuting zones cover only counties within one state. Around 17 percent (119) cover two states, while more than 1 percent (8) cover three states. In terms of labor force, the first group accounts for 71 percent, the two state for 26 and the three state commuting zones for 3 percent of total U.S. labor force, i.e., overlap with multiple states is correlated with higher labor force size.

7 DISCUSSION

Contribution The novelty of our results is in documenting that microtasking is accessible to a wider public than other online labor markets. Specifically, we leverage the granular nature of microtasks to shed new light on how the labor supply for microtasking varies with unemployment and across time of day. Our results highlight that, when unemployment is rising, microtasking platforms attract people in areas with an older population that has lower educational attainment. These findings substantiate the claim that workers with a wide range of educational levels perceive online labor as an option for generating income in times of unemployment – beyond the usual notion of a side activity. Lastly, we use a unified approach to study how unemployment interacts with participation and engagement in microtasking, and the associated labor supply elasticities in one single framework.

Implications for policy and research We consider our insights useful for several reasons. First, OLM and microtasking are likely to become more important, as platforms are becoming more advanced and continue to be an important input for developing and training AI. We show that, even in an early stage (2011-2015), these platforms attracted interest of individuals. The number of workers turning to OLM has likely increased since 2015. We also expect to find that it intensified during the COVID-19 pandemic and will do so as well during other future economic crises. Farsighted regulators might wish to develop strategies for connecting online labor markets with more traditional forms of labor. Second, we highlight a clear pattern in which OLM for microtasks can attract low-skill workers. This insight allows platform operators to develop strategies for better targeting this population segment to enhance platform growth. More importantly, our findings suggest that OLM for microtasking can help in reducing regional mismatches between the demand for and supply of labor. This is relevant for policy makers who need to resolve regional skill mismatch without driving people to migrate. By doing so, OLM for microtasking could help in reducing interregional inequality and contribute to growth. Achieving these goals is of interest to many policymakers (see Kuek et al., 2015; Rossotto et al., 2012). Finally, low retention rates (in the form of a weak connection between unemployment and the number of incumbent active users) suggest that workers did not find microtasking attractive enough to engage with the platform over a long period. This result might reflect the 'duality of empowerment and marginalization' discussed by Deng and Joshi (2016) and Deng et al. (2016). Although microtasking offers great freedom, flexibility, and open access to work, the need to "curate" their portfolio of tasks might favor educated "part-time microworkers" (Ipeirotis, 2010; Difallah et al., 2018). Lastly, our results concerning wage elasticities and their relation to unemployment are informative for policymakers who wish to reform tax-benefit policy (Bargain et al., 2014). Platform stakeholders can use these insights to assess platform growth given current economic conditions.

Limitations and future research Our research has a few caveats that further research should be able to overcome. First, we do not have access to individual-level data. Although we included available labor market and demographic data, the ability to observe users' earnings outside the platform, demographic background, or detailed unemployment data by demographic group would be ideal. Future research that can use individual-level data could address these questions, which are of great interest.

Second, our analysis is limited to a single platform, at an early stage. Future research on other comparable platforms and more recent data would shed precious light on whether our findings persist. Moreover, we highlight low retention rates in the online market for microtasks before 2015,[27] but welcome more research about retention rates and work that compares our findings to related online platforms, for example, for ride hailing or food delivery.

Third, in this study we had access to data only on US workers. They compete for tasks with many other workers worldwide, and these other workers often come from countries with a lower cost of living and hence a lower reservation wage. Future work could analyze the role of global competition among workers in developed vs. developing countries in the operation of the platform, and use different skill sets across user groups to as identifying variation in worker behavior.

A fourth limitation is that we cannot study *why* the unemployment rate is related to the labor supply elasticity. Two mechanisms might drive the results: changes in preferences, or effect heterogeneity among demographic groups might change the composition of workers who participate in OLM in times of high unemployment. Changes in preferences for online labor occur when rising unemployment changes the value of outside options, such as the expected return of offline job search, for the same individual. Alternatively, if unemployment drives particular groups of individuals to the platform, changes in the demography of online workers

[27] Recent work on microtasks on Amazon Mechanical Turk by Ipeirotis (2010) and Difallah et al. (2018) estimated longer worker half lives, highlighting the need for further research on what causes the difference in results.

might be the reason for changes in online labor supply.[28] Disentangling the different possible mechanisms and user behaviors would be fruitful ground for further research.

Lastly, our findings suggest a pattern in which low-skill workers in regions with high unemployment turn to microtasking during normal working hours, which we interpret as an effort to substitute for income losses related to high unemployment. Although a pattern of unemployed workers using microtasking as a substitute seems the most plausible interpretation, we cannot provide ultimate proof of this mechanism without individual-level data on earnings and employment status. We welcome future research that can incorporate this additional layer of information and provide additional insights into the underlying mechanisms.

8 CONCLUSION

The relationship between unemployment and the adoption of OLM for microtasks is not obvious. Although OLM could be attractive to unemployed workers in need of income, structurally weak regions tend to be characterized by slower technology adoption and limited access to online markets. In this paper we study the relationship between unemployment and workers' adoption of microtasking. We use data from a large microtasking platform combined with administrative data on unemployment. We apply an identification strategy based on Bartik-type industry shift shares.

We find that high unemployment makes microtasking more attractive to users in regions with an older, predominantly male, and white population and a low share of college graduates. This is the opposite of previous findings on high-skill online labor, and reflects the structural differences between these two forms of online labor. The effect on participation is transient and does not affect the number of active incumbent users. At the intensive margin, higher unemployment leads to increased microtasking activity during normal working hours, suggesting a pattern of labor substitution. Moreover, the online labor supply becomes more elastic with an increase in the unemployment rate. Workers are not very sensitive to wage changes, but they react more if the unemployment rate is high.

Together, our findings highlight that workers started experimenting with microtasking platforms shortly after the great recession. We document that microtasking is an appealing online

[28] For example, users with outside options that have a lower value might want to work more hours, might check the platform more regularly for lucrative jobs, or they might try to be online at times when there are fewer other users.

option for low-skill workers, who were more likely to use microtasking to substitute for other types of employment. However, OLM for microtasks did not permanently substitute for offline work during our period of observation, as documented by the low retention rates.

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APPENDICES

A Diagnostics for the Bartik IV

Table A1: OLS and first stage regression results – Extensive Margin

	OLS Results		First Stage results	
	Reg. Users	Active Users	Reg. Users	Active Users
	(1)	(2)	(3)	(4)
Unemployment Rate	1.314***	1.671*		
	(0.508)	(0.896)		
Bartik Shock			-0.059***	-0.052***
			(0.011)	(0.012)
Offline wage	-0.054***	-0.022	-0.001*	-0.001**
	(0.010)	(0.014)	(0.000)	(0.000)
% age 15-24 (i)	-6.563***	0.274	0.068	-0.006
	(1.558)	(3.132)	(0.067)	(0.071)
% age 45-64 (i)	-0.161	4.467	-0.200***	-0.155
	(1.726)	(3.990)	(0.075)	(0.094)
% male (i)	-4.215	-13.393	0.932***	1.549***
	(4.170)	(10.561)	(0.221)	(0.240)
% white (i)	4.336*	-13.004**	-0.482***	-0.418***
	(2.339)	(5.146)	(0.110)	(0.112)
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
Observations	13140	10950	13140	10945

NOTE: The table shows the OLS results (col. (1) and (2)) and the first stage (col. (3) and (4) for the two-stage least squares estimation results shown in Table 2. Standard errors in parentheses are clustered by commuting zone and robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Rotemberg weights. We compute Rotemberg weights of the Bartik estimator with controls, aggregated across time periods. As Goldsmith-Pinkham et al. (2020, p. 2611) point out, "... these weights give a way of describing the research design that reflects the variation in the data that the estimator is using, and hence makes concrete for the reader what types of deviations from the identifying assumption are likely to be important."

The results are in Table A2. We find that the distribution of sensitivity is skewed, so that a small number of instruments have a large share of the weight. Table A2 shows that the top five instruments account for over fifty percent (0.635/1.208=.526) of the positive weight in the estimator.[29] These top five instruments are "Support activities for mining, and oil and gas extraction" (2131), "Fruit and Tree Nut Farming" (1113), "Seafood Product Preparation and Packaging" (3117) and "Garment Pressing, and Agents for Laundries and Drycleaners" (7212) and "Federal and Federally-Sponsored Credit Agencies" (6111). In our setting, we hence compare places with varying greater and smaller shares of oil and gas extraction. This analysis confirms that the industries with low-skill work play a large role in the Bartik instrument.

[29] Compare the sum of α_k in Panel D with the sum of positive weights reported in Panel A.

We also note that Panel B shows that the national growth rates (g_k) are weakly correlated (-0.009) with the sensitivity-to-misspecification elasticities (α_k). Hence, the growth rates provide a poor guide to understanding what variation in the data drives estimates. In contrast, the elasticities are reasonably related (0.295) to the variation in the industry shares across locations ($Var(z_{l,k})$). As outlined by the treatment of Goldsmith-Pinkham et al. (2020), we rely on the exogenous shares assumption of the Bartik instrument, i.e. that conditional on observables, the commuting zone-specific industry shares are exogenous to *changes* in the error term (e.g. innovations to platform activity).[30]

Plausibility of the identifying assumption. While the identifying assumptions cannot be tested directly, we check their plausibility in different ways. We note first that in our setting there is no pre-period and so it is not possible to test for parallel pretrends without further assumptions. Second, we test for correlates of the industry shares with commuting zone characteristics. Table A3 shows the relationship between 2011/Q1 characteristics of commuting zones and the share of the top 5 industries in Table A2, as well the overall Bartik instrument. First, the R^2 in these regressions is moderate: for example, we can explain 10 percent of the variation in share of the "Oil and Gas Extraction" via our covariates. Second, we find that some of our Top 5 industries are statistically significantly correlated with the share of older and male population.

Overidentification and Heterogeneity. We follow Goldsmith-Pinkham et al. (2020) and implement alternative estimators which allow to test for overidentification. In Table A4 we report a series of OLS and IV specifications, with various sets of control variables. First, the IV estimates are bigger than OLS estimates. Second, the Bartik results are sensitive to the inclusion of controls, though these are not statistically distinguishable. Where appropriate we report overidentification tests. TSLS with the Bartik instrument and the overidentified TSLS and LIML are substantially smaller. The different point estimates suggest the presence of misspecification. In column 4 we see that the overidentification tests reject the null that all instruments are exogeneous. While the failure of the overidentification tests could indicate misspecification, it can also point to heterogeneity (Goldsmith-Pinkham et al., 2020). We investigate these two possibilities in Figure A1, which shows some of the heterogeneity in treatment effects underlying the overall Bartik estimate (Figure A2 shows the relationship between the Rotemberg weights and the first-stage F-statistic). First, the figure shows that among the "high-powered" (i.e., those with a first stage F-statistic above five) industries, there is substantial dispersion around the Bartik $\hat{\beta}$. Second, the industries with the largest weights do tend to be closest to the overall Bartik $\hat{\beta}$. Third, the patterns of heterogeneity suggest that there are likely to be negative weights on some of the underlying location-specific coefficients. In particular, there is substantial dispersion in the $\hat{\beta}_k$ and some of the outlier $\hat{\beta}_k$ have negative weights. Thus, the underlying location-specific effects (the β_l) that lead to a negative coefficient likely receive negative weights so that the overall Bartik estimate does not reflect convex weights. To see this more generally, the Panel E of Table A2 shows that the mean of the β_k among the negative weight industries is very different than the mean of the β_k among the industries with positive weights.

[30] See Goldsmith-Pinkham et al. (2020, p. 2598.).

Table A2: Summary of Rotemberg Weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.208	-0.001	0.147
Positive	1.208	0.007	0.853

Panel B: Correlations of Industry Aggregates

	α_k	g_k	β_k	F_k	Var(z_k)
α_k	1				
g_k	-0.009	1			
β_k	-0.004	0.076	1		
F_k	0.134	0.042	-0.011	1	
Var(z_k)	0.295	-0.074	-0.009	-0.042	1

Panel C: Variation across time in α_k

	Sum	Mean
2011	.141	.0001
2012	.179	.0001
2013	.163	.0001
2014	.158	.0001
2015	.360	.0003

Panel D: Top 5 Rotemberg weight industries

	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	95 % CI	Ind Share
Oil + gas extraction	0.243	-0.114	-0.653	(-6.30,3.90)	0.306
Fruit and Tree Nut Farming	0.174	0.058	10.134	(-10.00,10.00)	0.178
Seafood	0.081	-0.041	6.936	(-1.80,10.00)	0.021
Pressing Laundries Drycleaners	0.069	0.470	-1.152	(-10.00,7.10)	0.029
Credit Agencies Industry	0.068	0.283	40.912	(-10.00,10.00)	4.874

Panel E: Estimates of β_k for positive and negative weights

	α-weighted Sum	Share of overall β	Mean
Negative	0.697	0.094	1.233
Positive	6.706	0.906	31.470

NOTE: This table reports statistics about the Rotemberg weights as implemented in Goldsmith-Pinkham et al. (2020) in Table 1 (canonical setting). Panel A reports the share and sum of negative weights. Panel B reports correlations between the weights (α_k), the national component of growth (g_k), the just-identified coefficient estimates (β_k), the first-stage F-statistic of the industry share (F_k), and the variation in the industry shares across locations ($Var(z_k)$). Panel C reports variation in the weights across years. Panel D reports the top five industries according to the Rotemberg weights. The g_k is the national industry growth rate, $\hat{\beta}_k$ is the coefficient from the just-identified regression, the 95 percent confidence interval is the weak instrument robust confidence interval using the method from Chernozhukhov and Hansen (2008) over a range from -10 to 10, and *Ind.Share* is the industry share (multiplied by 100 for legibility). Panel E reports statistics about how the values of β_k vary with the positive and negative Rotemberg weights.

Table A3: Relationship between Industry Shares and Characteristics

	2131	1113	3117	7212	6111	Bartik
Offline wage	0.009***	0.000	0.001	-0.000*	-0.000	0.009***
	(3.60)	(0.29)	(1.00)	(-2.24)	(-0.19)	(8.14)
% age 15-24 (i)	-0.023	-0.010	0.010	-0.013	0.239**	-0.036
	(-0.49)	(-0.66)	(0.72)	(-1.69)	(2.87)	(-0.48)
% age 45-64 (i)	-0.184**	-0.032	0.043	0.016*	0.399***	-0.079
	(-2.71)	(-1.61)	(1.42)	(2.53)	(4.13)	(-1.13)
% male (i)	-0.075	-0.039	0.065	0.040**	0.277	-0.390**
	(-0.44)	(-1.37)	(1.43)	(3.27)	(1.19)	(-2.70)
% white (i)	0.042***	0.006*	-0.007	-0.002*	-0.049*	-0.011
	(4.22)	(2.03)	(-1.79)	(-2.44)	(-2.36)	(-0.74)
% at least bachelor	-0.315***	-0.017	-0.004	0.013**	-0.089*	-0.084**
	(-5.18)	(-1.74)	(-0.42)	(3.08)	(-1.98)	(-2.65)
% local FB friends	-0.142***	-0.013*	-0.004	-0.003*	0.017	-0.016
	(-4.81)	(-1.99)	(-0.83)	(-2.36)	(0.54)	(-1.04)
Constant	0.140	0.040	-0.047	-0.018**	-0.218	0.055
	(1.44)	(1.55)	(-1.33)	(-3.14)	(-1.46)	(0.65)
Observations	655	655	655	655	655	655
R^2	0.254	0.008	0.042	0.217	0.068	0.210

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

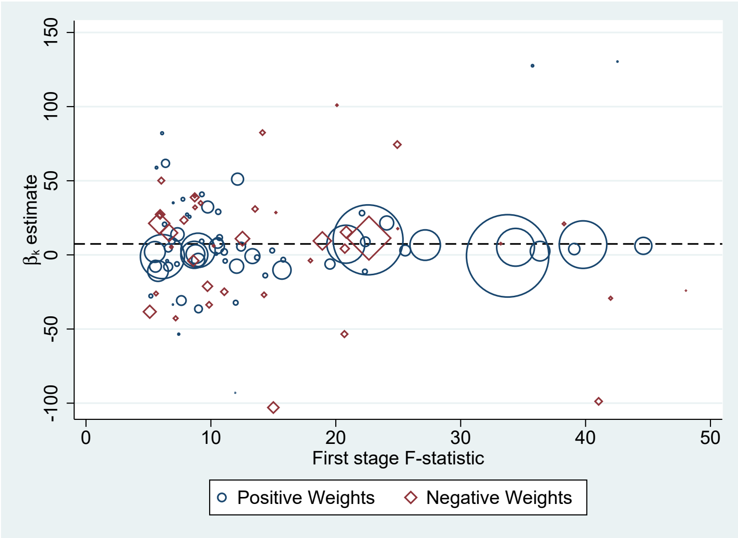
NOTE: Each column reports results of a single regression of a 2010 industry share on 2011 Q1 characteristics. The final column is the Bartik instrument.

Table A4: OLS and IV estimates

	Unempl. Rate		Coeff equal	Over ID test
	(1)	(2)	(3)	(4)
OLS	0.988	1.314	[0.52]	
TSLS (Bartik)	10.374	11.385	[0.80]	
TSLS	2.107	2.930	[0.39]	370.67[0.01]
LIML	2.345	3.274	[0.40]	370.40[0.01]
Year and CZ FE	Yes	Yes		
Controls	No	Yes		
Observations	13140	13140		

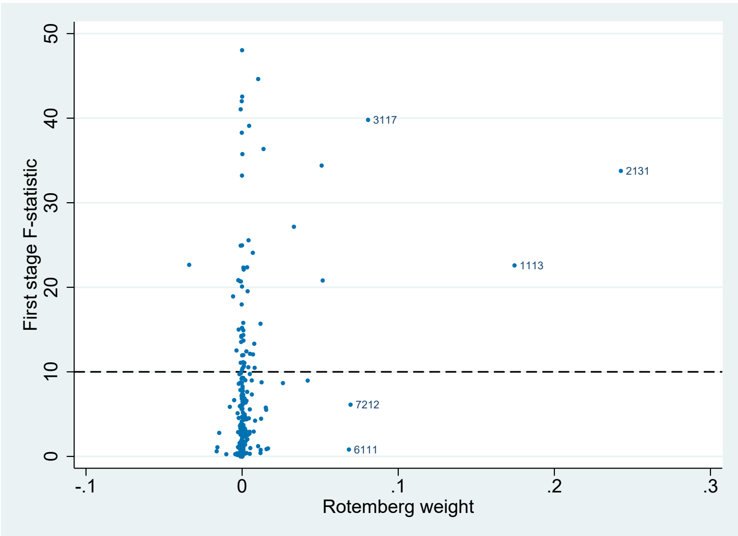
NOTE: This table reports a variety of the coefficient of the unemployment rate. The dependent variable are quarterly registrations in a commuting zones, and the specification is as in the main body of the paper. Column 1 does not contain controls, while column 2 does. The TSLS (Bartik) row uses the Bartik instrument. The TSLS row uses each industry share (multiplied with the growth rates) separately as instruments. The p-value in column 3 for the equality of coefficients compares the adjacent columns with and without controls. The controls are as in the main paper.

Figure A1: Heterogeneity of β_k



NOTES: This figure plots the relationship between each instruments' β_k, first stage F-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figure plots the estimated β_k^{hat} for each instrument on the y-axis and the estimated first-stage F-statistic on the x-axis. The size of the points are scaled by the magnitude of the Rotemberg weights, with the circles denoting positive Rotemberg weights and the diamonds denoting negative weights. The horizontal dashed line is plotted at the value of the overall β^{hat} reported in the second column in the TSLS (Bartik) row in Table A4. The figure excludes instruments with first-stage F-statistics below 5 and above 75.

Figure A2: First stage versus Rotemberg weights



NOTES: This figure plots each instrument's Rotemberg weight against the first stage F-statistic. Each point represents the estimates for an instrument, where instruments are aggregated across time periods following Section 3.3. The labelled industries correspond to the five highest Rotemberg weight industries from Table A2. The dashed horizontal line is equal to 10. The figure excludes instruments with first-stage F-statistics above 75.

B Full Hourly Decomposition

B.1 Volume of tasks by hour of the day

Table B1: Volume of tasks by hour of the day, only weekdays (coefficient for 4

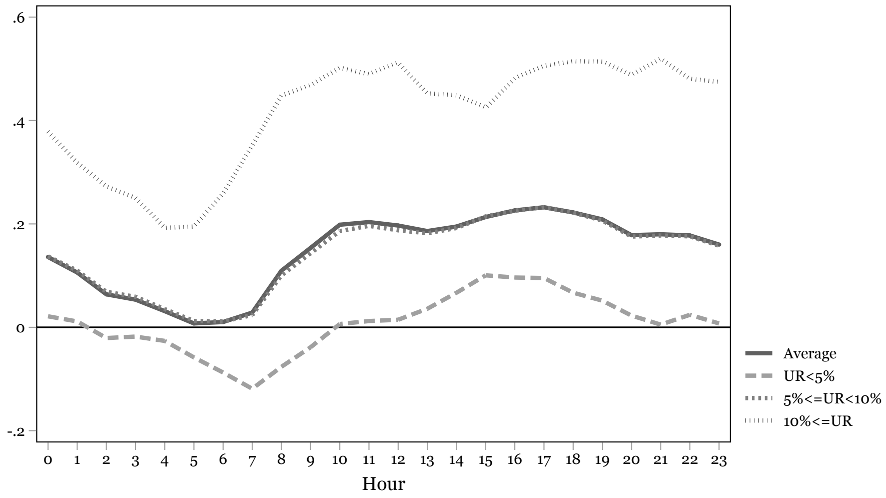
Variable	Coefficient	S.E.	Variable	Coefficient	S.E.
Platform wage	0.127***	(0.007)			
Hour 0	Reference		Hour 0 × UR	0.388	(1.588)
Hour 1	0.022	(0.031)	Hour 1 × UR	-0.666	(1.632)
Hour 2	-0.023	(0.045)	Hour 2 × UR	-0.855	(1.670)
Hour 3	-0.051	(0.057)	Hour 3 × UR	-0.959	(1.751)
Hour 4	-0.128*	(0.066)	Hour 4 × UR	-0.648	(1.866)
Hour 5	-0.235***	(0.077)	Hour 5 × UR	0.312	(1.966)
Hour 6	-0.460***	(0.070)	Hour 6 × UR	3.037	(1.875)
Hour 7	-0.661***	(0.076)	Hour 7 × UR	5.546***	(1.853)
Hour 8	-0.681***	(0.084)	Hour 8 × UR	6.725***	(1.895)
Hour 9	-0.559***	(0.097)	Hour 9 × UR	5.911***	(1.931)
Hour 10	-0.501***	(0.074)	Hour 10 × UR	6.098***	(1.810)
Hour 11	-0.290***	(0.081)	Hour 11 × UR	4.329**	(1.735)
Hour 12	-0.169**	(0.077)	Hour 12 × UR	3.263*	(1.729)
Hour 13	0.025	(0.071)	Hour 13 × UR	1.064	(1.713)
Hour 14	0.186***	(0.065)	Hour 14 × UR	-0.217	(1.679)
Hour 15	0.329***	(0.051)	Hour 15 × UR	-1.233	(1.560)
Hour 16	0.304***	(0.050)	Hour 16 × UR	-0.470	(1.558)
Hour 17	0.198***	(0.044)	Hour 17 × UR	0.743	(1.522)
Hour 18	0.032	(0.047)	Hour 18 × UR	1.848	(1.582)
Hour 19	-0.128***	(0.046)	Hour 19 × UR	3.070*	(1.612)
Hour 20	-0.238***	(0.051)	Hour 20 × UR	3.712**	(1.625)
Hour 21	-0.314***	(0.053)	Hour 21 × UR	4.625***	(1.682)
Hour 22	-0.268***	(0.045)	Hour 22 × UR	4.092**	(1.619)
Hour 23	-0.144***	(0.038)	Hour 23 × UR	2.482	(1.591)
R^2 Overall	0.31		CZ FE	Yes	
R^2 Within	0.41		Year Quarter FE	Yes	
Observations	358794		Task complexity	Yes	

NOTE: The table shows regressions of the effect unemployment on the activity in the online labor market by the hour of the day. The dependent variable is the logged number of tasks done on the platform during week days. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

B.2 Decomposition of wage elasticities by hour of the day

Figure B1 visualizes the profile of the respective average labor supply elasticities for different levels of unemployment and by the hour of the day. Unemployment rates are grouped in intervals. The predicted values based on the regression results in Table B3 show that there is considerable variation in labor supply elasticities across the day. For low regional unemployment rates below 5 percent we predict negative labor supply elasticities from 2am to 10am. For average unemployment rates the elasticities are strictly positive and we find the highest elasticities in the afternoon.

Figure B1: Labor Supply Elasticities by Hour of the Day



NOTE: The graph shows predicted wage elasticities of labor supply over the hours of the day for different levels of the unemployment rate. Calculations are based on the estimation results provided in Table B3.

Table B3: Full hourly decomposition

	(1) All	(2) All	(3) During Week	(4) Weekend
Platform wage	-0.043*	-0.032	-0.033	-0.053**
	(0.022)	(0.022)	(0.024)	(0.022)
Wage X UR	1.040***	0.909***	0.931***	1.004***
	(0.189)	(0.194)	(0.204)	(0.212)
Wage X Hour 1	-0.003	0.003	0.001	0.011
	(0.002)	(0.008)	(0.008)	(0.014)
Wage X Hour 2	-0.012***	0.001	-0.011	0.039***
	(0.003)	(0.009)	(0.009)	(0.013)
Wage X Hour 3	-0.014***	0.004	-0.006	0.037***
	(0.003)	(0.009)	(0.010)	(0.014)
Wage X Hour 4	-0.021***	0.004	-0.005	0.033**
	(0.004)	(0.011)	(0.011)	(0.016)
Wage X Hour 5	-0.026***	-0.011	-0.023*	0.023
	(0.004)	(0.011)	(0.012)	(0.016)
Wage X Hour 6	-0.028***	-0.036***	-0.043***	-0.015
	(0.004)	(0.011)	(0.013)	(0.016)
Wage X Hour 7	-0.027***	-0.060***	-0.072***	-0.028
	(0.005)	(0.013)	(0.014)	(0.017)
Wage X Hour 8	-0.012**	-0.054***	-0.059***	-0.039**
	(0.005)	(0.014)	(0.015)	(0.016)
Wage X Hour 9	-0.003	-0.036***	-0.041***	-0.025
	(0.004)	(0.014)	(0.015)	(0.019)

Wage X Hour 10	0.007*	-0.019	-0.017	-0.026
	(0.004)	(0.012)	(0.013)	(0.018)
Wage X Hour 11	0.009**	-0.016	-0.016	-0.020
	(0.004)	(0.013)	(0.014)	(0.015)
Wage X Hour 12	0.008***	-0.013	-0.015	-0.013
	(0.003)	(0.011)	(0.012)	(0.015)
Wage X Hour 13	0.008***	-0.000	0.001	-0.005
	(0.003)	(0.009)	(0.011)	(0.013)
Wage X Hour 14	0.010***	0.018**	0.019*	0.014
	(0.003)	(0.009)	(0.011)	(0.012)
Wage X Hour 15	0.016***	0.031***	0.034***	0.020
	(0.003)	(0.009)	(0.010)	(0.013)
Wage X Hour 16	0.019***	0.028***	0.028***	0.024*
	(0.003)	(0.009)	(0.009)	(0.015)
Wage X Hour 17	0.021***	0.025***	0.026***	0.020
	(0.002)	(0.008)	(0.008)	(0.012)
Wage X Hour 18	0.022***	0.017**	0.010	0.038***
	(0.003)	(0.007)	(0.008)	(0.012)
Wage X Hour 19	0.017***	0.008	0.002	0.030**
	(0.002)	(0.007)	(0.008)	(0.013)
Wage X Hour 20	0.011***	-0.004	-0.010	0.016
	(0.002)	(0.008)	(0.009)	(0.014)
Wage X Hour 21	0.011***	-0.013*	-0.023***	0.019
	(0.002)	(0.007)	(0.008)	(0.012)
Wage X Hour 22	0.010***	0.001	-0.009	0.031***
	(0.002)	(0.007)	(0.009)	(0.011)
Wage X Hour 23	0.007***	-0.014**	-0.018**	-0.003
	(0.002)	(0.007)	(0.007)	(0.012)
Wage X Weekend	-0.011***	-0.025***		
	(0.001)	(0.003)		
Wage X UR X Hour 1		-0.093	-0.086	-0.113
		(0.094)	(0.100)	(0.180)
Wage X UR X Hour 2		-0.179	-0.059	-0.562***
		(0.118)	(0.131)	(0.163)
Wage X UR X Hour 3		-0.259**	-0.143	-0.609***
		(0.120)	(0.133)	(0.169)
Wage X UR X Hour 4		-0.360**	-0.261*	-0.676***
		(0.150)	(0.158)	(0.208)
Wage X UR X Hour 5		-0.211	-0.098	-0.549***
		(0.154)	(0.168)	(0.202)
Wage X UR X Hour 6		0.103	0.156	-0.072
		(0.155)	(0.182)	(0.205)
Wage X UR X Hour 7		0.436**	0.580***	0.029
		(0.177)	(0.190)	(0.227)
Wage X UR X Hour 8		0.534***	0.624***	0.290
		(0.172)	(0.187)	(0.191)
Wage X UR X Hour 9		0.420***	0.491***	0.227
		(0.153)	(0.163)	(0.223)
Wage X UR X Hour 10		0.318**	0.297**	0.405*
		(0.138)	(0.143)	(0.214)
Wage X UR X Hour 11		0.315**	0.306**	0.352*
		(0.139)	(0.154)	(0.180)
Wage X UR X Hour 12		0.269**	0.296**	0.235
		(0.127)	(0.137)	(0.178)
Wage X UR X Hour 13		0.104	0.095	0.151
		(0.112)	(0.131)	(0.159)
Wage X UR X Hour 14		-0.100	-0.083	-0.115
		(0.107)	(0.122)	(0.146)
Wage X UR X Hour 15		-0.196*	-0.213*	-0.119
		(0.109)	(0.125)	(0.145)
Wage X UR X Hour 16		-0.104	-0.083	-0.143
		(0.102)	(0.103)	(0.177)

Wage X UR X Hour 17		-0.041	-0.038	-0.021
		(0.096)	(0.104)	(0.153)
Wage X UR X Hour 18		0.062	0.144	-0.176
		(0.084)	(0.098)	(0.156)
Wage X UR X Hour 19		0.118	0.200**	-0.149
		(0.084)	(0.098)	(0.162)
Wage X UR X Hour 20		0.185**	0.255**	-0.016
		(0.088)	(0.102)	(0.169)
Wage X UR X Hour 21		0.312***	0.433***	-0.048
		(0.084)	(0.093)	(0.152)
Wage X UR X Hour 22		0.116	0.228**	-0.231
		(0.089)	(0.111)	(0.149)
Wage X UR X Hour 23		0.274***	0.316***	0.154
		(0.090)	(0.094)	(0.152)
Wage X UR X Weekend		0.174***		
		(0.034)		
Category Dummies	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
R^2 Overall	0.16	0.16	0.17	0.15
R^2 Within	0.18	0.18	0.19	0.18
Observations	486814	486814	358794	128020

NOTE: The table shows regressions of unemployment on the activity in the online labor market by the hour of the day. The dependent variable is the logged odds ratio for working hours. Col. 1 shows the distribution of activity across the day, and in columns (2)-(4) we introduce interactions of wage and the daily hours with unemployment. We separately show our results for all days of the week (col. 1-2), and then separately for regular weekdays (col. 3) and weekends (col. 4). Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

C Alternative specifications and other robustness checks

Table C1: Results on the Extensive Margin, Instrumented with Bartik IVs (log-log)

	Reg. Users First (1)	Reg. Users Second (2)	Active Users First (3)	Active Users Second (4)	Active Users (New) (5)	Active Users (Old) (6)
Bartik shock	-0.719***		-0.662***			
	(0.131)		(0.141)			
ln(UR)		0.789**		0.516	0.888**	0.559
		(0.323)		(0.368)	(0.364)	(0.342)
Offline wage	-0.038***	-0.015	-0.036***	-0.026	-0.013	0.008
	(0.007)	(0.016)	(0.006)	(0.018)	(0.017)	(0.016)
% age 15-24 (i)	-1.921**	-5.275***	-2.385***	-2.200	0.467	-5.520*
	(0.756)	(1.803)	(0.832)	(2.515)	(2.128)	(3.053)
% age 45-64 (i)	-4.639***	1.683	-5.050***	3.982	2.990	10.773***
	(0.0865)	(2.261)	(1.113)	(3.236)	(2.714)	(3.557)
% male (i)	5.199**	-4.957	11.022***	-15.697*	-13.467**	-23.559**
	(2.305)	(4.979)	(2.466)	(8.579)	(6.707)	(9.460)
% white (i)	-2.252	4.561*	-1.034	-0.483	0.817	-10.742***
	(1.374)	(2.495)	(1.538)	(3.331)	(2.787)	(4.154)
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13140	13140	10954	10945	10945	10945
Kleibergen-Paap Stat		30.21		22.11	22.11	22.11

NOTE: This table replicates the findings in Table 2 with a Log-Log specification. The dependent variable measures the logarithm of newly registered users (col. (2)), all active users on the platform (col. (4)). Columns 5 and 6 separately consider newly registered users who were active in the quarter (col. (5)) and active users who had registered in past quarters (col. (6)). Unemployment enters as $ln(unemployment\ rate * 100)$ and is instrumented by the Bartik shock. The first stage for the two-stage least squares estimation results in col. (2) and (4) are in col. (1) and col. (3), respectively. All regressions are two-stage least squares fixed effects regressions. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Table C2: Results Newly Registered Users, Instrumented with Bartik IVs (log-log)

	(1)	(2)	(3)	(4)	(5)	(6)
ln(UR)	0.789**	0.593*	0.736**	0.779**	0.855***	0.695**
	(0.323)	(0.330)	(0.334)	(0.329)	(0.326)	(0.349)
Offline wage	-0.015	-0.031**	0.000	-0.013	-0.013	-0.015
	(0.016)	(0.016)	(0.017)	(0.015)	(0.015)	(0.017)
% age 15-24 (i)	-5.275***	-5.629	-4.580**	-3.997**	-3.610*	-5.723***
	(1.803)	(4.145)	(1.804)	(1.884)	(2.004)	(1.844)
% age 45-64 (i)	1.683	-10.694***	-2.120	2.526	1.716	-0.908
	(2.261)	(3.795)	(2.573)	(2.096)	(2.336)	(3.123)
% male (i)	-4.957	-4.501	-35.741***	-2.397	0.113	-6.821
	(4.979)	(4.805)	(8.123)	(5.729)	(4.953)	(4.928)
% white (i)	4.561*	8.174***	3.485	3.505	12.088***	3.425
	(2.495)	(2.700)	(2.492)	(2.846)	(3.307)	(2.699)
ln(%UR) * % age 15-24		1.833				
		(2.079)				
ln(%UR) * % age 45-64		6.895***				
		(1.819)				
ln(%UR) * % male			17.298***			
			(3.976)			
ln(%UR) * % white				0.650		
				(0.533)		
ln(%UR) * % education					-3.675***	
					(0.812)	
ln(%UR) * % local FB friends						-1.005*
						(0.603)
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13140	13140	13140	13140	13140	13100
Kleibergen-Paap Stat	30.21	9.45	15.24	15.43	18.18	18.90
Anderson-Rubin p-val.	0.01	0.00	0.00	0.00	0.00	0.00

NOTE: This table replicates the analysis from Table 3 using the log-log specification of column (1) in Table 3. The dependent variable measures log of newly registered users. All regressions are two-stage least squares fixed effects regressions. Regional unemployment is instrumented with Bartik instruments. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Table C3: Results on the Intensive Margin Labor Supply - log-log Specification

	OLS		IV	
			First	Second
	(1)	(2)	(3)	(4)
Platform wage	0.015***	-0.069**	2.155***	-0.645***
	(0.004)	(0.031)	(0.016)	(0.224)
Medium task complexity	-1.364***	-1.343***	-0.504***	-1.198***
	(0.039)	(0.040)	(0.025)	(0.067)
High task complexity	-2.296***	-2.284***	-0.260***	-2.203***
	(0.072)	(0.072)	(0.027)	(0.078)
ln(UR) X Wage		0.039***		0.303***
		(0.014)		(0.103)
Platf. wage X Bartik Shock			-0.596***	
			(0.027)	
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
Observations	16416	16416	16416	16416
Adjusted R^2	0.30	0.30		0.23
Model	fe	fe	fe	iv
Kleibergen-Paap Stat				14.71
Anderson-Rubin p-val.				0.00

NOTE: The table replicates Table 4, but the dependent variable measures the logarithm of working hours on Microworkers.com. Unemployment enters as $ln(unemployment\ rate * 100)$. Columns (1) and (2) are OLS fixed effects regressions, and column (4) is estimated by two stage least squares fixed effects. Column (3) is the first stage for the estimation in column (4) with the platform wage interacted with the regional unemployment rate as dependent variable. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Table C4: Robustness Check: Intensive Margin Labor Supply with instrumented wage

	(1) OLS	(2) IV	(3) OLS	(4) IV_WAGE	(5) IV_UR	(6) IV_ALL
Wage in CZ	-0.045***	0.019***	-0.078***	-0.007	-0.276***	-0.189**
	(0.002)	(0.004)	(0.008)	(0.012)	(0.043)	(0.087)
Medium task complexity	-1.311***	-1.419***	-1.303***	-1.406***	-1.259***	-1.315***
	(0.035)	(0.039)	(0.035)	(0.039)	(0.036)	(0.056)
High task complexity	-1.808***	-2.560***	-1.810***	-2.503***	-1.818***	-2.110***
	(0.067)	(0.094)	(0.067)	(0.098)	(0.071)	(0.209)
Wage in CZ X UR			0.425***	0.271**	2.926***	2.143**
			(0.087)	(0.117)	(0.526)	(0.888)
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16416	16416	16416	16416	16416	16416
Adjusted R^2	0.37	0.24	0.38	0.26	0.18	0.25
Model	fe	iv	fe	iv	iv	iv
Kleibergen-Paap Stat		488.68		199.25	37.24	4.51
Anderson-Rubin p-val.		0.00		0.00	0.00	0.00
Wage Elasticity	-0.56	0.24	-0.58	0.17	-0.70	-0.35
at UR < 5%			-0.62	0.04	-1.58	-1.03
at 5% <= UR < 10%			-0.59	0.16	-0.76	-0.40
at 10% <= UR < 20%			-0.47	0.39	1.03	0.97
at UR >= 20%			0.38	0.77	5.83	4.43

NOTE: The dependent variable measures the logged odds ratio of working hours on Microworkers.com. Columns (1) and (3) are OLS fixed effects regressions. Columns (3), (4) to (6) are estimated by two-stage least squares fixed effects, with "Wage in CZ" being instrumented by average wages achieved in other commuting zones (columns 2, 4, and 6). In columns 5 and 6, the unemployment rate in the interaction is further instrumented by our Bartik instrument. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Table C5: Robustness check: Intensive Margin Labor Supply - Number of Tasks

	(1) OLS	(2) OLS	(3) IV
Platform wage	0.047***	-0.044	-0.373**
	(0.003)	(0.031)	(0.173)
Medium task complexity	-1.938***	-1.915***	-1.832***
	(0.039)	(0.040)	(0.058)
High task complexity	-3.561***	-3.548***	-3.502***
	(0.072)	(0.072)	(0.075)
ln(UR) X Wage		0.042***	0.193**
		(0.014)	(0.079)
Year Quarter FE	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes
Observations	16416	16416	16416
Adjusted R^2	0.47	0.48	0.44
Model	fe	fe	iv
Kleibergen-Paap Stat			14.71
Anderson-Rubin p-val.			0.00

NOTE: The table replicates Table 4, but uses the log number of completed tasks on Microworkers.com as the dependent variable. Columns (1) and (2) are OLS fixed effects regressions and column (3) is estimated by two-stage least squares fixed effects. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

Table C6: Robustness check: Including only single-state commuting zones

	Reg. Users (1)	Active Users (2)	Active Users (New) (3)	Active Users (Old) (4)
Unemployment Rate	1.461***	1.598	1.972**	0.444
	(0.523)	(0.985)	(0.968)	(1.011)
Offline wage	-0.046***	-0.015	-0.018	0.009
	(0.010)	(0.015)	(0.014)	(0.015)
% age 15-24 (i)	-7.169***	-0.378	2.139	-3.678
	(1.556)	(3.400)	(3.145)	(4.135)
% age 45-64 (i)	-0.785	5.305	3.803	9.991**
	(1.776)	(4.294)	(3.805)	(4.657)
% male (i)	-5.705	-22.963**	-10.830	-31.558**
	(4.500)	(11.513)	(11.210)	(12.939)
% white (i)	6.113**	-20.959***	-18.182***	-32.149***
	(2.481)	(5.163)	(4.697)	(6.003)
Year Quarter FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
R^2 Overall	0.01	0.00	0.00	0.02
R^2 Within	0.08	0.58	0.63	0.61
Observations	10660	8702	8702	8702
UR elasticity	0.10	0.08	0.10	0.02
Offl. Wage elast.	-0.44	-0.11	-0.14	0.07

NOTE: This table replicates Table A1 but includes only commuting zones that are entirely within the borders of a single state. The dependent variable measures the logged odds-ratio of newly registered users (Col. (1)), all active users on the platform (col. (2)). Columns (3) and (4) separately consider newly registered users who were active in the quarter (col. (3)) and active users that registered in past quarters (col. (4)). All regressions are two stage least squares fixed effects regressions. First-stage results are provided in Table A1. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * p <0.1, ** p <0.05, *** p <0.01.

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ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de