# Unemployment and online labor: Evidence from microtasking

MIS Quarterly

RESEARCH ARTICLE

# UNEMPLOYMENT AND ONLINE LABOR: EVIDENCE FROM MICROTASKING[1]

**Ulrich Laitenberger**
Tilburg School of Economics and Management (TiSEM), Tilburg University, THE NETHERLANDS,
and ZEW, Mannheim, GERMANY {u.m.laitenberger@uvt.nl}

**Steffen Viete**
KfW Research, Frankfurt am Main, GERMANY {steffen.viete@kfw.de}

**Olga Slivko**
Rotterdam School of Management, Erasmus University, Rotterdam, THE NETHERLANDS {slivko@rsm.nl}

**Michael Kummer**
University of East Anglia, Norwich, UNITED KINGDOM
and ZEW, Mannheim, GERMANY {M.Kummer@uea.ac.uk}

**Kathrin Borchert**
University of Würzburg, Würzburg, GERMANY {kathrin.borchert@informatik.uni-wuerzburg.de}

**Matthias Hirth**
Technical University of Ilmenau, Ilmenau, GERMANY {matthias.hirth@tu-ilmenau.de}

*We analyze the relationship between unemployment and the supply of online labor for microtasking. Using detailed U.S. data from a large microtasking platform between 2011 and 2015, we study the participation and the number of hours supplied by workers in the U.S. We found 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-skilled workers. Our analyses of the intensive margin, wage elasticity, and temporal work patterns suggest that the increased participation was likely motivated by an effort to substitute income. Our findings suggest that microtasking platforms are an interesting online labor market for less educated workers. However, we also observed very low retention rates, indicative of a solely transient participation effect.*

**Keywords:** Crowdworking, online platform, unemployment, wage elasticity

## 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. During the COVID-19 pandemic, online tools for coordination and communication displayed an impressive ability to overcome these frictions to sustain a wide range of economic activity, at least temporarily.[2] This phenomenon 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 affected the adoption of OLM for microtasks described in our section "Background: Microtasking Platforms." Microtasks are small, well-defined jobs such as video screening, transcription,

[1] Corey Angst was the accepting senior editor for this paper. Miguel Godinho de Matos served as the associate editor. JEL classification numbers: J21, D29, D80, H41, J60, L17

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

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 U.S. $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 online labor market 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 & 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 tasks and the fact that every action is observed facilitate a detailed analysis of workers' labor supply choices.

We used internal platform data from Microworkers.com, a large U.S.-based online labor market for microtasks, presented in the "Data" section. We analyzed how regional unemployment in the U.S. affects the labor supply (registrations, engagement) on this platform. We used data on platform activity by U.S. workers for the period 2011 to 2015 and combined them with data on unemployment from the Bureau of Labor Statistics.

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 addressed 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 commuting zones (e.g., internet infrastructure) and for nationwide shocks affecting adoption. Moreover, we used Bartik-style instrumental variables (IV) to account for the endogeneity of local unemployment and changes in these variables. We used a structural labor supply model to measure wage elasticities. This approach created 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 conducted 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 caused more individuals to join the platform and complete tasks. A one-percentage-point increase in regional unemployment led to a 11.4% increase in the number of newly registered users and a 9.6% increase in new active users on the OLM for microtasks. However, the increase in registrations was not accompanied by a significant increase in the number of active incumbent users.

Second, when unemployment increased, more users registered 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 found higher unemployment to coincide with increased microtasking activity, especially during normal working hours, suggesting a pattern of labor substitution. Moreover, the online labor supply became more elastic with an increase in the unemployment rate. Workers did not react very strongly to wage changes but were more sensitive to higher wages when the unemployment rate was high, consistent with low retention rates.

Overall, we make three contributions on which we provide further details in our "Discussion" section. 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 when work is performed. We leveraged this potential to study substitution across both time of day and a wide range of tasks. Our framework allowed us to study both the extensive margin (participation) and the intensive margin (engagement), as well as how variation in the elasticity of substitution varies with the level of unemployment.

## Related Literature

Our work relates to three broad streams of literature. First, a large stream of literature is interested in substitution patterns between economic activity online and offline in general, and in labor markets specifically. A 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 has addressed 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 & 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 & Zhu, 2014; Xu et al., 2014), hotels and accommodations (Zervas et al., 2017), finance (Xue et al., 2011; Luo & Zhang, 2013; Agrawal et al., 2015a; Lin and Viswanathan, 2016), and even in hate crimes (Chan et al., 2016; Müller & Schwarz, 2020). Other research has explored 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) have provided recent overviews of this literature. Few studies have analyzed the relationship between unemployment and participation in OLM. Clearly, microtasking OLM could be particularly attractive for those who are under- or unemployed. Whereas freelancing requires specific (domain) skills, and workers have to maintain appropriate skill levels (Kokkodis, 2021; Kokkodis & Ipeirotis, 2016), learning and acquiring new skills is a defining feature of (and motivating factor for) microtasking (Chandler & Kapelner, 2013; Chandler & Shapiro, 2016). Hence, because microtasks are divisible and require less skill, the entry barriers to this segment of online markets are much lower (Kuek et al., 2015; Katz & Krueger, 2017). Using data from a survey on the microtasking platforms Amazon Mechanical Turk and Crowdflower, Berg (2015) showed 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) documented similar shares of the previously unemployed among those providing labor for Amazon Mechanical Turk. Using checking account data, Farrell and Greig (2016) highlighted that people resort to OLM after experiencing negative income shocks. Perhaps most closely related to our work, Huang et al. (2020) analyzed how unemployment affects the labor supply of freelancers. They documented a connection between unemployment and participation in OLM for complex "macrotasks," such as software development. They found that participation increased by 21.8% following a 1% 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 conducted a causal analysis, in which we substantiated existing descriptive and survey-based evidence on whether unemployment drives 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 move to online work in our paper is not based on a worker's offline background, as in freelancing, and occurs in a global labor market. Our findings are therefore novel, because they specifically document that OLM are of interest to unemployed workers 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 & 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 has focused 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 has documented 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) showed that workers on the microtasking platform Crowdflower achieve 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 & Chilton, 2010; Ipeirotis, 2010; Kaufmann et al., 2011; Teodoro et al., 2014). Other motivations include the high levels of autonomy, fairness, accountability, and the possibility of making an impact (Deng & Joshi, 2016), as well as entertainment and learning (Ipeirotis, 2010; Brabham, 2010; Chandler & Kapelner, 2013; Schnitzer et al., 2015; Chandler & Shapiro, 2016; Kost et al., 2018; Keskinen et al., 2021). Several surveys aimed to better understand 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 & Furrer, 2019; Mourelatos et al., 2020; Jiang et al., 2021). Martin et al. (2017) conducted surveys on the platforms Amazon Mechanical Turk, Crowdee and Microworkers.com. They discussed the demographic distribution at Amazon Mechanical Turk, finding that the majority of workers are U.S. residents (50%-60%). In line with other studies, they showed 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 appear 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 the geographic mobility of labor (Niebuhr et al., 2012; Artuc et al., 2015). Although OLM help to mitigate offline labor market frictions, they can impact income distribution and inequality (Gefen & 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 employers predominantly in high-income countries and contractors mainly in low-income countries. Because of superstar (long-tail) effects, OLM might benefit contractors with vertically differentiated (i.e., high-quality performers) or horizontally differentiated skills (i.e., niche performers) or lower-cost performers, while those characterized by mediocre quality, common skills, or higher costs are disadvantaged (Agrawal et al., 2015b). This effect is amplified when ratings do not reflect category-specific experience and workers cannot build category-specific reputations (Kokkodis & 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 populations, (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.

## 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 & 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 that *aggregate* hundreds or thousands of microtasks, which are performed by multiple suppliers (Kaganer et al., 2013). Microtasks are well-defined jobs that typically take between several seconds and 20 minutes and require only very basic quantitative or reading skills (Deng & 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, high levels of flexibility, and worker autonomy can be highly attractive for crowdworkers and bear the promise of a transformed work context (Deng & Joshi, 2016). At the same time, crowdworkers often work alone, with little social contact and security, meaning 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, and 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 & 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 such platforms, but the World Bank estimated that as of 2012, microtasking already generated between $450 and $900 million annually, with an overall employment of between 1.45 and 2.9 million workers (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). The International Labor Organisation (ILO) and the European Commission consider it to be a relevant platform for studies (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. 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, and 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 geolocated 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 micropayment 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 ratio of successful vs. nonsuccessful tasks. To be able to continue performing tasks, employees must keep their success rate above 75%.

### *Microworkers.com in Comparison with Other Platforms*

Hirth et al. (2011) compared Microworkers.com to Amazon Mechanical Turk, showing that crowdworkers are less U.S. centered on Microworkers.com than on Amazon Mechanical Turk. This conclusion is in line with contemporary and more recent analyses of the demographics of workers on Amazon Mechanical Turk (Ipeirotis, 2010; Difallah et al., 2018). Thus, working hours can be different on average. However, U.S. 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% of employers account for 70% of the wage bill, compared to 90% of the wage bill on Amazon Mechanical Turk. Hirth et al. (2011) argued that this is due to Amazon Mechanical Turk being used more by mediators for other companies, whereas 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.

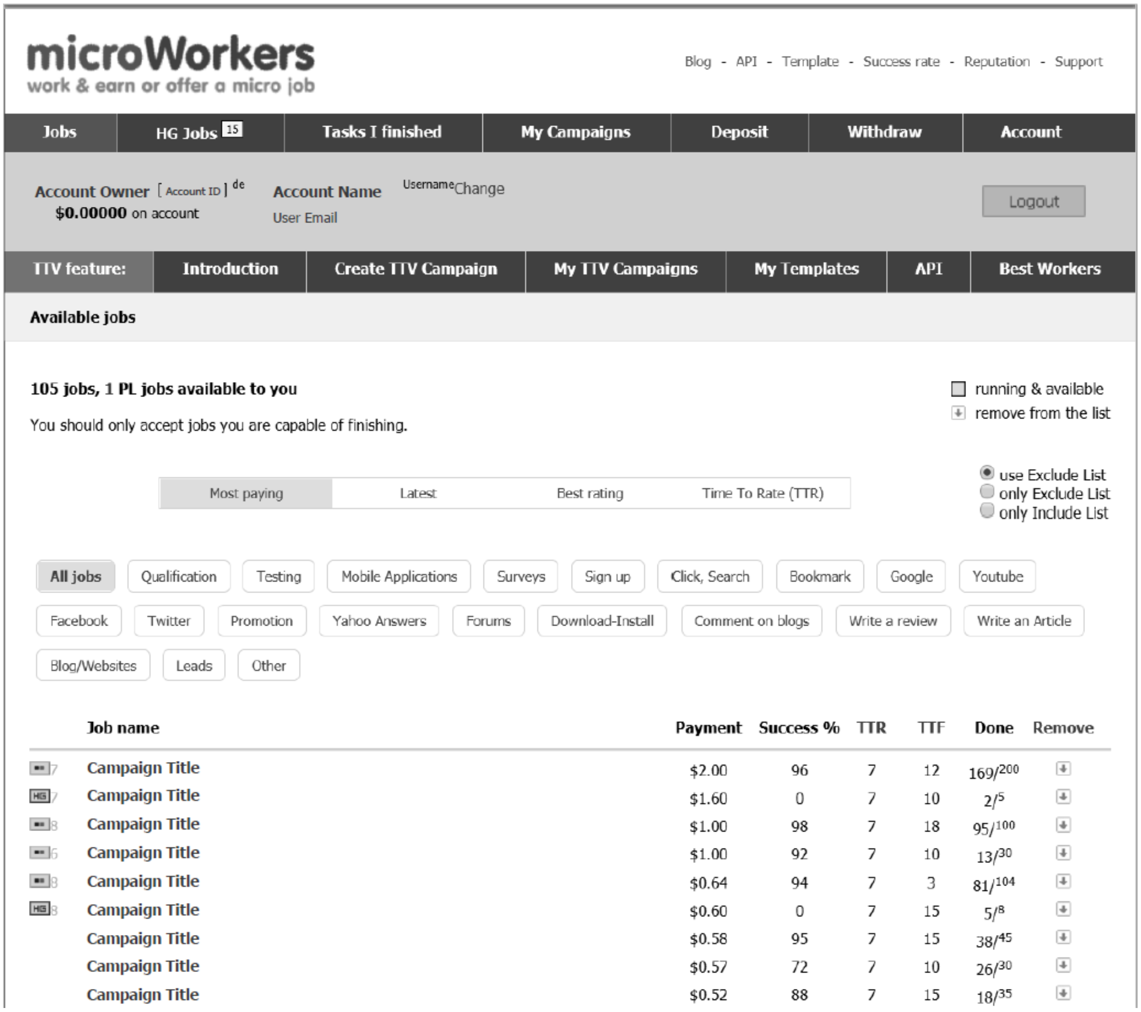



**Figure 1. Screenshot of the Microworkers.com Marketplace**

A study commissioned by the International Labor Organization (Berg et al., 2018) conducted a descriptive comparison between the platforms. They highlight that Microworkers.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 U.S. Amazon Mechanical Turkers is lower (52%) than overall on Microworkers.com (68%). Forty-four percent of U.S. Amazon Mechanical Turk workers have a bachelor's or post-graduate degree, compared to 48% 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 lower incomes could imply lower average reservation wages and a more competitive remuneration on Microworkers.com.

## The Data

### *Data Set Creation*

We combined information on platform activity with administrative data on U.S. local labor markets. We used internal platform data from Microworkers.com on the activity of U.S. workers between January 2011 and December 2015. We augmented 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 used data on wages and employment by industry from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW). We complemented this data with information on local demographics from the Annual County Resident Population Estimates by the U.S. Census Bureau.[3]

We aggregated the data to commuting zones as defined by the U.S. Department of Agriculture (Tolbert & Sizer, 1996; Autor et al., 2013).[4] Commuting zones represent clusters of counties with strong commuting ties. After merging the data from 709 potential commuting zones with our platform data, we obtained a sample of 657 local labor markets with 20 quarterly observations between January 2011 and December 2015. The final data set contained 13,140 commuting zone quarter observations.

We used 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.[5] Finally, for our analysis of time allocation in our subsection "Activity at the Intensive Margin," we added further information about the date and time of task completion.

## *Descriptive Statistics*

Table 1 displays the descriptive statistics for 20 quarterly observations of 657 commuting zones for the regressors and outcome variables used in the analysis. The variables are organized into three groups: Panel A shows the aggregate participation and activity of U.S. 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. For reasons of confidentiality, we normalized all variables containing information on the platform (Panel A) by their maximum value across the commuting zone and time and multiplied them 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 previously ("old"). We used different measures for work volume transacted over the platform, which is (1) the total number of "tasks," (2) the amount of "working hours" spent on these tasks (as indicated by the employer), and (3) the total "wage sum." To measure how much users engage in tasks, we mainly made use of "working hours" as a fraction of disposable time.[6] In the analysis of labor supply at the intensive margin, we calculated 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 was 24.6% higher than for low complexity, and the hourly wage for "high" complexity tasks was 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 those for the measures of volumes. Moreover, some commuting zones showed no activity in some periods. We consider periods with no activity in the extensive margin analyses in subsection "Registrations and Activity (Extensive Margin)" but not in the intensive margin analyses in subsection "Activity at the Intensive Margin."[7]

In addition to the variables characterizing platform activity, we added several control variables regarding labor force characteristics (Panel B) and population demographics (Panel C). The average commuting zone in our estimation sample had a population size of 387,512 and a labor force size of 236,755. The average unemployment rate in our sample was around 7%.

[3] 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 interpolated the yearly data in order to match them to our quarterly data.

[4] For the aggregation of county-level data to commuting zones, we used the 2000 version of the crosswalk files provided by the U.S. 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 U.S. Census Bureau, the U.S. Centers for Disease Control and Prevention, and David Dorn (http://www.ddorn.net/data.htm).

[5] We define low-complexity tasks as tasks that 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 on a blog post. 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.

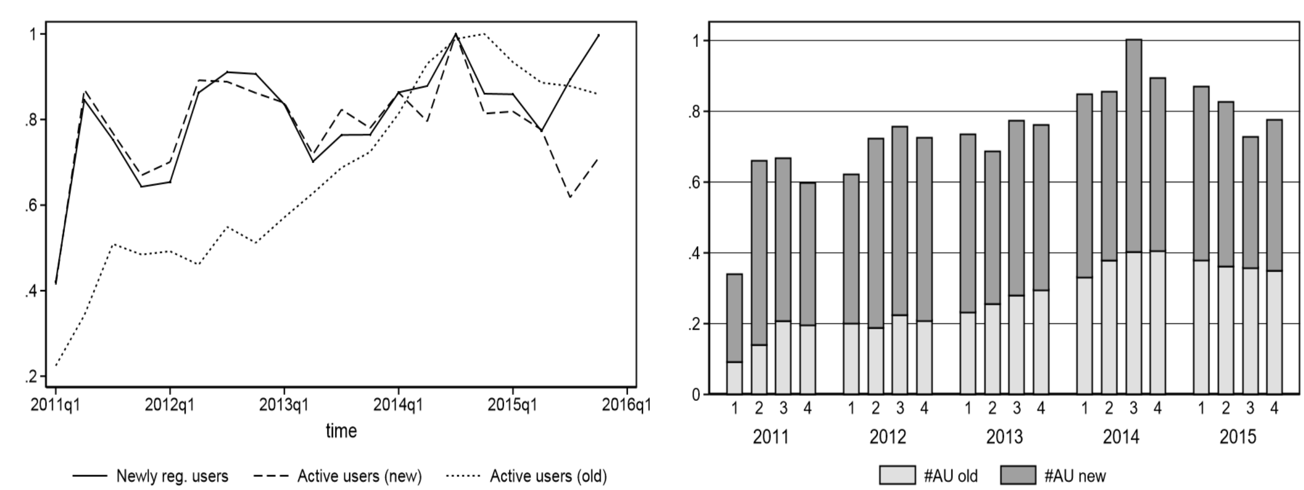
[6] Working hours could be reported inaccurately by employers. However, our findings are qualitatively unaffected when measuring work volume by the number of tasks. This analysis was included in Appendix C of an earlier version and is now omitted to save space. It is available upon request.

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

**Table 1. Descriptive Statistics**

| | Mean | *SD* | 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 (men) | 0.39 | 0.78 | 0.01 | 8.70 |
| Labor force (men) | 0.24 | 0.60 | 0.00 | 9.04 |
| Unemployment rate | 0.07 | 0.03 | 0.01 | 0.29 |
| Offline wage in commuting zone | 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's | 0.21 | 0.07 | 0.07 | 0.51 |
| % local FB friends | 0.52 | 0.11 | 0.17 | 0.77 |
| Observations | 13140 | | | |

**Note:** (i) indicates that data were only available yearly and were therefore linearly interpolated to the quarter level.




**Note:** Active users are defined as users that performed at least one task in the respective quarter. Values are normalized by the maximum value.

**Figure 2. Aggregate Participation and Activity of U.S. Residents on Microworkers.com**

The average quarterly wage per employee in the commuting zone (off-platform) was U.S. $9,634. We distinguished three age groups from 15 to 65 years, with the middle group aged 25-44.[8] The average share of males was 50%, while, on average, the share of white population was 84%. Following Huang et al. (2020), we added further information on educational attainment measured by the share of individuals in the year 2012 that obtained a university or college degree (at least a bachelor's). We accounted for the dispersion of social connections by the share of Facebook friends residing within a distance of 50km, as first proposed in Bailey et al. (2018).

## *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 the aggregate participation and activity of U.S. residents on the Microworkers.com 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 grew until 2014 but then saw a small decrease in 2015. We further look at the distribution of registered users over commuting zones in Figure 3. The map plots quintiles of the ratio of all registered users during our observation period over the size of the labor force in 2016. Dark regions correspond to the highest quintile and light regions the lowest. As expected, activity in the online labor market is concentrated on the east and the west coast of the U.S.

## *Methodology and Identification*

### Model

In our empirical application, workers make two decisions. First, they decide whether to register and work on the platform (extensive labor supply); 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).

To use this methodology, we needed 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 considered all members of the labor force in a commuting zone as potential workers, and assumed that they could use all their available time to work on the platform.[9]

In the following, we first analyzed the workers' choice of *whether* to register and become active on the platform (extensive margin). Subsequently, we used 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 other options, such as off-platform work. We define the potential microworker $i$'s conditional indirect utility $u_{i,c,t}^{Entry}$ from joining the platform as

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

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 time-varying commuting zone characteristics, $UR_{c,t}$ is the local unemployment rate, $\xi_c$ is a commuting zone and $\xi_t$ a time fixed effect, and $\epsilon_{i,c,t}$ are unobserved shocks that are independently and identically extreme value-distributed.

Workers make their 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 $\xi_t$, so that we could not include it explicitly. We closely followed the standard discrete-choice approach as outlined in Berry (1994) and summed up the workers' individual entry decisions to obtain aggregated choices at our level of observation.

[8] Note that on Microworkers.com, users must be a minimum of 18 years old (See https://www.microworkers.com/terms.php). Nevertheless, we selected 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 youngest group. We used the age group information from the total population, as detailed labor force data was not available.

[9] An alternative approach would be using counts of registrants and task volumes in an ordinary least squares (OLS) approach. While this yields similar results, it does not account for fluctuations in the size of the population and different lengths of time periods, which can lead to measurement errors. We omitted the corresponding results to save space, but can provide them upon request.

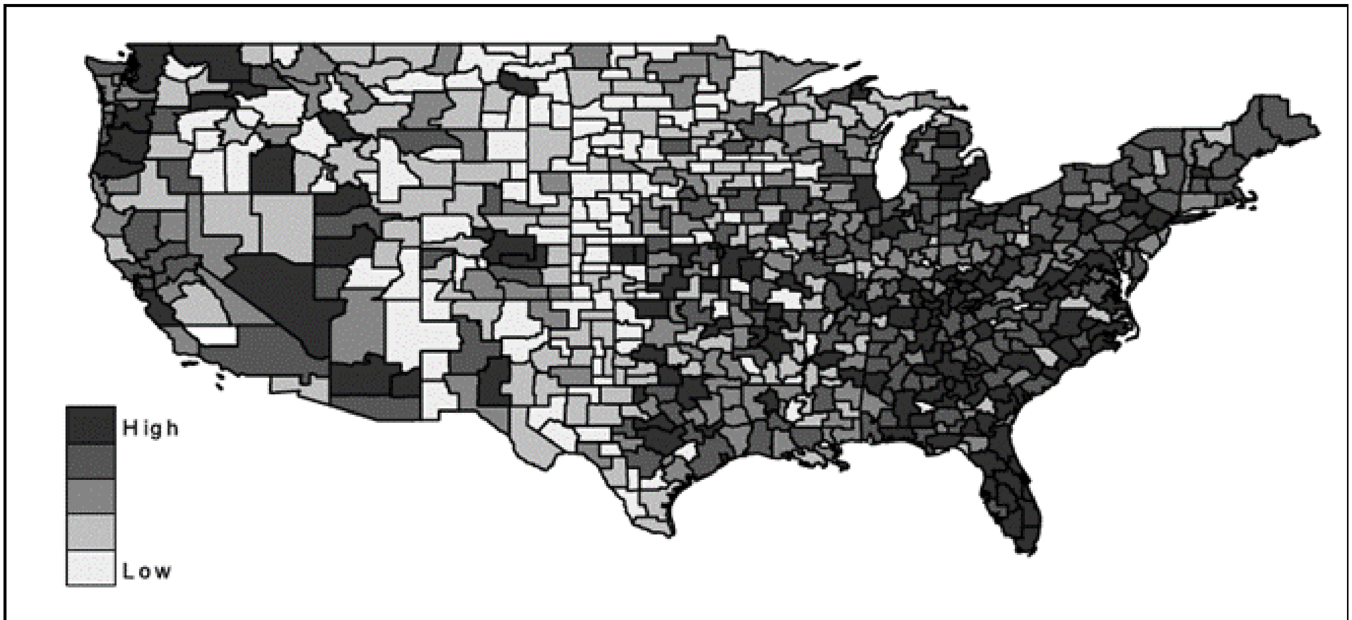



**Figure 3. Geographic Distribution of Registered User**

This approach resulted in a tractable linear estimation equation.[10] 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:

$$ln(s_{c,t}{}^{Entry}) - ln(s_{0;c,t}{}^{Entry}) = X_{c,t}\alpha + \beta UR_{c,t} + \xi_c + \xi_t + \varepsilon_{c,t}, \quad (1)$$

where $s_{c,t}$ is the share of individuals in a commuting zone $c$ that register on the platform in quarter $t$ or perform at least one task in that quarter. The variable $s_{0;c,t}$, in turn, is the share of individuals living in commuting zone $c$ that chose not to register in quarter $t$. We estimated Equation (1) for the number of newly registered and the number of active users, differentiated by newly active and incumbent users. We calculated the elasticity of the online labor supply at the extensive margin with regard to the unemployment rate, given by

$$\frac{UR_{c,t}}{s_{c,t}} \frac{\partial s_{c,t}}{\partial UR_{c,t}} = \eta_{UR} = \beta UR_{c,t}(1 - s_{c,t}). \quad (2)$$

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

[10] For a detailed exposition and the mathematical derivation, see Equations (10) to (14).

### Task Performance by Registered Users (Intensive Margin)

In the second step, we modeled 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, implying 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 off-platform 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 they have fewer 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 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:

$$u_{i,j,t} = X_{j,t}\alpha + \beta w_{j,t} + \gamma w_{j,t} UR_{c,t} + \xi_c + \xi_t + \epsilon_{i,j,t}, \quad (3)$$

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. $\xi_c$ is a commuting zone and $\xi_t$ is a time fixed effect. The vector $\alpha$ captures valuations by individuals for task characteristics, $\beta$ is the marginal utility of the wage when the unemployment rate, $UR_{c,t}$, is at zero, $\gamma$ 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 off-platform option captures other work opportunities online or offline as well as the option of not working at all. The off-platform option is normalized so that it has a mean conditional utility of zero: $u_{i,0,t} = \epsilon_{i,0,t}$.

Since we used aggregate data, we only observed 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 $s_{i,j,t}$. To achieve a linear specification, we (again) applied the inversion steps suggested by Berry (1994), yielding the following regression equation:

$$ln(s_{c,j,t}) - ln(s_{c,0,t}) = X_{c,j}\alpha + \beta w_{j,t} + \gamma w_{j,t} UR_{c,t} + \xi_c + \xi_t + \varepsilon_{j,t}, \quad (4)$$

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 off-platform activities.[11] Note that this equation does not include the unemployment rate as a stand-alone variable, since it is not task specific.[12]

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

After estimating the model, we calculated the elasticity of task supply with respect to the wage by:

$$\frac{w_{j,t}}{s_{c,j,t}} \frac{\partial s_{c,j,t}}{\partial w_{j,t}} = \eta_w = (\beta + \gamma UR_{c,t}) w_{j,t} (1 - s_{c,j,t}) \quad (5)$$

and then built the average over observations.

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

### *Endogeneity of Unemployment as a Threat to Identification.*

The main threat to identification in our study is due to unobserved factors that could drive both the unemployment rate and participation on the microtasking platform. Such factors could be structural differences between commuting zones such as a less-developed internet infrastructure, which relates to a high unemployment rate but also limits participation online. As long as these factors vary little over the four years of our observation period, a potential omitted-variable bias could be mitigated by employing commuting zone fixed effects. Another concern would 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 can also mitigate a potential concern of variation in the competition from outside the U.S. 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 used 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.[13] Note first that endogeneity due to reverse causation is unlikely due to the minor relevance that any single online labor platform—even Amazon's MTurk—played for the

[11] 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 toward the external good.

[12] Variables that are not task specific reflect a constant on workers' utility within a choice set; the coefficients in this model are identified for their scale but not their level. We also estimated reduced-form models to evaluate the impact of including the unemployment rate as a stand-alone variable. The results—included in an earlier version of the paper—were omitted to save space, but are available upon request.

[13] We did not expect local labor *demand* to correlate with platform work, as the tasks mediated over Microworkers.com have no true counterpart in "offline" employment.

overall economy during the period under study.[14] A larger concern would arise if unobservable worker and infrastructure characteristics within a commuting zone could be correlated with both the unemployment rate and working online. The following example illustrates this potential problem: If unemployment increases, younger individuals might move out of the commuting zone. If younger individuals are also more likely to engage in online work, the effect of unemployment on working online would be underestimated. Similar examples for other demographic and infrastructural characteristics can be easily constructed.[15]

## Use of Bartik Instruments

We dealt with this concern using an instrumental variable approach. We instrumented the commuting-zone-level unemployment rate using a predicted commuting-zone-level unemployment rate, which combines national-level growth rates across industries with differences in the initial industrial structure across commuting zones. This instrument can isolate a measure of local labor demand that is unrelated to local labor supply. It therefore allowed 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 & Katz, 1992; Bound & Holzer, 2000; Autor & Duggan, 2003; Autor et al., 2013; Kroft & Notowidigdo, 2016; Adelino et al., 2017) or migration (Altonji & Card, 1991). Gould et al. (2002); Fougère et al. (2009) and Brown and De Cao (2018) used Bartik shocks to identify the causal effects of regional unemployment.

## Construction of the Instrument

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

$$\pi_{ct} = \sum_{k=1}^{K} \gamma_{c,k,t_0} \left( \frac{E_{-c,k,t} - E_{-c,k,t-1}}{E_{-c,k,t-1}} \right), \tag{6}$$

where $\gamma_{c,k,t_o}$ is the employment share of industry $k$ in commuting zone $c$ and base period $t_0$ and $E_{-c,k,t-1}$ is the respective national employment excluding commuting zone $c$ in the previous period $t$-1.

## 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 population relative to the U.S. as a whole (there are 657 commuting zones in the U.S.). Furthermore, the strategy also relies on the assumption that the industry structure is exogenous to the application. While the initial industry structure might correlate 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 relied on predetermined, time-invariant industry shares (based on 2010), and controlled 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 allowed us to understand which industries drove 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.[16] 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

[14] 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.

[15] 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 effect of unemployment on working online.

[16] At the end of our period of observation, Microworkers.com introduced a tool that allows employers to restrict workers from selected cities, but this change only affected two months of our data.

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 U.S. are unlikely to influence wages on the platform, because the share of U.S.-American workers on the platform is simply too small.[17]

## Results

In what follows, we first study the extensive margin of online labor supply, which is the number of workers that joined the platform and became active (see subsection "Registrations and Activity (Extensive Margin)"). After that, we turn to the intensive margin of labor supply which relates to the amount of time the average worker spent on the platform (see subsection "Activity at the Intensive Margin").

### *Registrations and Activity (Extensive Margin)*

We estimated how unemployment affects the participation of workers on the platform using Equation 2. We used our data on all commuting zones and quantified users' participation using new registrations and activity in commuting zone $c$ and period $t$. We instrumented unemployment using Bartik shocks to account for the endogeneity of the unemployment rate (cf. subsection "Endogeneity of Unemployment as a Threat to Identification"). We report the OLS results without correcting for this endogeneity in Table A1 in Appendix A.

#### Baseline Results

In Table 2 we show the baseline regression. The dependent variable measured the logged odds ratio of newly registered users (Column 1) and all active users on the platform (Column 2). Columns 3 and 4 further distinguish active users that registered in the same quarter ("new') and those who had signed up previously ("old"). All regressions were estimated using the two-stage least squares fixed effects model. First-stage OLS results are provided in Table A1. 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.[18] According to our estimates, a 1% increase in regional unemployment led to a 0.8% increase in the number of newly registered users and a 0.67% increase of newly active users in the OLM.

The labor supply elasticity with respect to unemployment for low-skill microtasks is significantly smaller than that 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, with a one-percentage-point increase in the unemployment rate, the number of registered users increased by 11.4%. This is nearly half the increase of 21.8% that was found for high-skilled freelancing jobs (Huang et al., 2020).[19]

#### Comparison of OLS and IV Results and Diagnostics

Before analyzing how these results vary across different demographic groups, we take note of 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 increased the magnitude of the labor supply elasticity with respect to unemployment compared to the OLS estimates. This is in line with our expectation because unemployment shocks tend to be larger in structurally weak regions with slower technology adoption. Since workers from economically weaker regions with less robust employment participate 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 as in the "canonical setting" described in Goldsmith-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).

[17] Even though U.S. workers were the fourth-largest user group on Microworkers.com at the beginning of our observation period (Hirth et al., 2011), their share of all registered workers was only 11%, and it is plausible that they also did fewer tasks than workers from other top-ranking countries.
[18] 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.
[19] Note, however, that our dependent variable is an odds ratio while Huang et al. (2020) used 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 of that found by Huang et al. (2020).

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

| | (1) Regular 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 |
| Commuting zone FE | Yes | Yes | Yes | Yes |
| Observations | 13140 | 10945 | 10945 | 10945 |
| Kleibergen-Paap statistic | 27.02 | 18.05 | 18.05 | 18.05 |
| Unemployement rate elasticity | 0.80 | 0.40 | 0.67 | 0.46 |

**Note:** All regressions are two-stage least squares fixed effects regressions. Unemployment is instrumented with Bartik instruments. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (i) indicates that data were only available yearly and were therefore linearly interpolated to the quarter level.

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), "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 desynchronized business cycles and are dominated by occupations for which no high formal qualification is required. This is consistent with our finding that registrations increased especially where the population had a lower educational attainment, as we will discuss in the next paragraph. Moreover, we found that structural differences across regions strongly explain regional 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 rejected the null hypothesis, which is likely the result of heterogeneity in how likely it is that workers from different industries will substitute other work with 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.

## 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).[20] Column 3 shows the interaction with the share of men, 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.[21] Compared to the reference age group of 25 to 44, the relationship between regional unemployment and registrations is significantly stronger in commuting zones with a larger share of workers 45 to 64 years old. There is no significant difference compared to the base group for the age bracket of 15-24. Furthermore, the relationship is stronger in regions with a higher share of men and white individuals. Importantly, the relationship between unemployment and platform sign-ups is stronger in commuting zones with a lower share of university graduates.

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

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

**Table 3. Results Newly Registered Users, Instrumented with Bartik IVs**

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

**Note:** All regressions are two-stage least squares fixed effects regressions. Unemployment is instrumented with Bartik instruments. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (i) indicates that data were only available yearly and were therefore linearly interpolated to the quarter level.

These results highlight an important difference to prior studies on the demographics of 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 have 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 Huang et al.'s (2020) finding, 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.

### *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 estimated 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 (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 in period $t$ as the numerator. This quantity was 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.[22]

### 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 found a moderate average wage elasticity of 0.15. This is in line with prior literature that has found a lower elasticity for the supply of online labor (Horton & Chilton, 2010; Dube et al., 2018, 2020) than for offline employment.[23] 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 idea that their opportunity cost is lower when they are 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.

As expected, the 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%.

### 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 standard errors that are too small (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.[24]

### 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 were driven by unemployed workers who substitute online labor for offline work, we would expect to see larger effects of regional unemployment on the online labor supply during regular working hours.[25] We augmented our data set with two additional variables: the weekday and hour of the day, as measured in the time zone of the worker. We then ran a regression with the logged number of tasks as the 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 the American Time Use Survey (ATUS)[26] with the temporal distribution of the tasks performed on Microworkers.com. While more than 60% of the regular employees begin work by 9 am in the ATUS data, activity on Microworkers.com peaks in the afternoon and continues until after midnight.

---

[22] We checked the robustness of our findings using an IV model that accounts for wage endogeneity. We used the local platform wage (at the commuting zone level) as an explanatory variable and instrumented it with achieved wages in other commuting zones. The results—included in an earlier version of the paper—were omitted to save space but are available upon request.

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

[24] Following the discussion by Angrist and Pischke (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 in 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, the Cragg–Donald Wald $F$-statistic (140.00) is well above the most stringent critical Stock-Yogo critical value suggested (Stock & Yogo, 2005).

[25] 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 were to experience a considerable drop in time constraints on the job during economic downturns.

[26] https://www.bls.gov/tus/home.htm

**Table 4. Results on the Intensive Margin Labor Supply**

| | OLS | OLS | IV | |
|---|---|---|---|---|
| | | | First | Second |
| | (1) | (2) | (3) | (4) |
| Platform wage | 0.016***<br>(0.004) | -0.013<br>(0.014) | 0.089***<br>(0.002) | -0.245**<br>(0.104) |
| Medium task complexity | -1.416***<br>(0.038) | -1.403***<br>(0.039) | -0.036***<br>(0.002) | -1.301***<br>(0.058) |
| High task complexity | -2.406***<br>(0.069) | -2.399***<br>(0.069) | -0.018***<br>(0.003) | -2.344***<br>(0.073) |
| Unemployment × Wage | | 0.320**<br>(0.140) | | 2.873**<br>(1.147) |
| Bartik Shock × Wage | | | -0.051***<br>(0.016) | |
| Year quarter FE | Yes | Yes | Yes | Yes |
| Commuting zone 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 statistic | | | | 9.94 |
| Cragg-Donald Wald *F* | | | | 140.00 |
| Anderson-Rubin *p*-value | | | 0.00 | |
| Wage elasticity | 0.16 | 0.11 | | -0.26 |
| at unemployment rate < 5% | | 0.00 | | -0.99 |
| at 5% ≤ unemployment rate < 10% | | 0.10 | | -0.31 |
| at 10% ≤ unemployment rate < 20% | | 0.32 | | 1.14 |
| at unemployment rate ≥ 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, and Column 4 is a two-stage least squares regression, with the respective first-stage results in column (3). Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

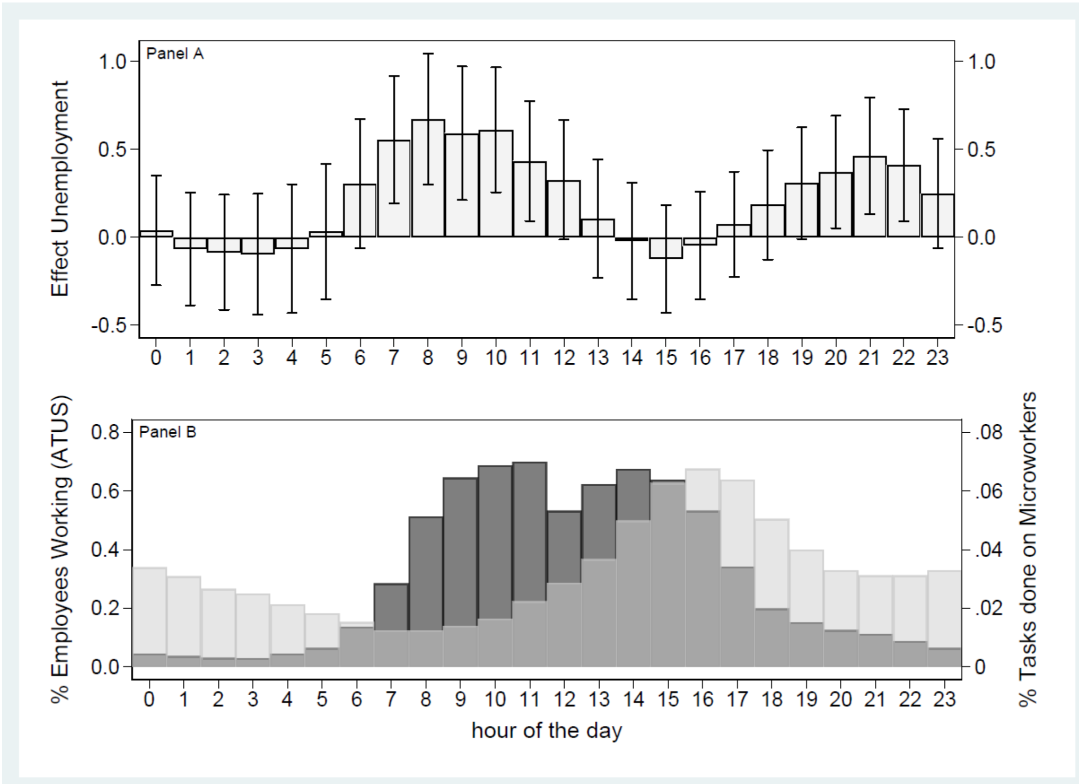



**Figure 4. Effect of Unemployment on Labor Supply by Hour of the Day**

**Note**: In Figure 4, Panel A shows the 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) (dark) and distribution of tasks performed on Microworkers.com (light gray). Over half the population is working by 8 am (ATUS). Most activity on Microworkers.com is from after noon to midnight.

Panel A visualizes the point estimates for the interaction terms of the hour of the day and the unemployment rate (for weekdays). The figure shows strong positive effects of unemployment on the online labor supply between 7 am and 11 am. This corresponds to the time of the day when the majority of individuals start their regular offline jobs according to ATUS.

In an additional analysis, we explored wage elasticities in all hours of the day, using our labor supply model. The results indicate that workers have a lower valuation for wages when working nights, after midnight, and on weekends (results are available upon request).[27] 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.

## *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 employed a different empirical specification; second, we allowed for the endogeneity of platform wages; third, we used different measures for labor supply; and fourth, we restricted our sample to commuting zones that do not span across any state borders. These analyses—included in an earlier version of the paper—were omitted to save space, but are available upon request.

[27] We analyzed interactions of the unemployment rate with the wage and hour-of-the-day indicators. The results show that the effect of unemployment is strongest outside regular working hours, between 7:00-12:00 and 20:00-0:00. Separately analyzing weekdays and weekends, we found that this effect occurs on weekdays rather than on weekends. Results are available upon request.

### Specification

The modeling structure in our estimations is based on knowing the number of all eligible workers who could participate on the platform, which allowed us to compute the shares of registered or active users (in analogy to a market share). While this structure provided us with a microfoundation for our estimation approach, the requirement of knowing the number of workers introduced potential measurement errors. To see whether our results are sensitive to our specification we estimated a log-log specification. The results, which are available upon request, show that our structural estimation results are very similar to regressions where we enter the respective dependent variable and the unemployment rate in logs. All results are qualitatively reproducible when using this alternative parametrization of our main variables of interest.

### Exogeneity of Platform Wage

In our analysis of the intensive margin, we used the global platform wage for each task category as an explanatory variable. As explained above, we held platform wage to be exogenous to the choices of the workers in any U.S. commuting zone, given that the share of workers from the U.S. was only 11%. In a robustness analysis, we used 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 were more prone to endogeneity issues, since users within the commuting zone self-selected 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 used the average wage in the category achieved in other commuting zones as an instrument. It varied in terms of employers' worldwide willingness to pay, while it was unaffected by changes in local reservation wages due to deteriorating local economic conditions offline. After instrumenting, the 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 used the raw number of tasks completed on Microworkers.com as an alternative measure for labor supply. Specifically, we replicated the regression analyses of Table 4 and found that our main findings remained qualitatively unchanged.

### Heterogeneity in Commuting Zones Spanning over Multiple States

In our data, we aggregated platform activity to commuting zones of which 18% spanned several states. This aggregation might have been problematic if there was heterogeneity in state-specific developments, which could have reduced 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 spanned multiple states. We therefore ran the estimations of Table 2 for commuting zones that were within one state only. The results imply nearly the same elasticities as found when using the full sample.

## Discussion

### *Contributions*

The novelty of our results lies in documenting that microtasking is accessible to a wider public than other online labor markets. Specifically, we leveraged the granular nature of microtasks to shed new light on how the labor supply for microtasking varies with unemployment and the time of day. Our results highlight that when unemployment rises, microtasking platforms attract new workers. The effect is larger 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 such labor as a side activity. Lastly, we used a unified approach to study how unemployment interacts with participation and engagement in microtasking and the associated labor supply elasticities in a 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 at an early stage (2011-2015), these platforms attracted the interest of individuals. The number of workers turning to OLM has likely increased since 2015. We also would expect to find that it intensified during the COVID-19 pandemic and that it will also do so during 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 of OLM for microtasks attracting low-skilled workers. This insight would allow platform operators to develop strategies to better target this population segment in order to enhance platform growth. More importantly, our findings suggest that OLM for microtasking can help reduce regional mismatches between labor supply and demand. This is relevant for policymakers seeking to resolve regional skill mismatches without driving people to migrate. Thus, OLM for microtasking could help reduce interregional inequality and contribute to growth. Achieving such goals should be 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 for workers 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 did not have access to individual-level data. Although we included available labor market and demographic data, the ability to observe users’ off-platform earnings, demographic background, or detailed unemployment data by demographic group would be ideal. Future research using individual-level data would therefore be of great value.

Second, our analysis was limited to a single platform at an early stage. Future research on other comparable platforms and more recent data would shed important light on whether our findings persist. Moreover, while we highlighted low retention rates in the online market for microtasks before 2015,[28] we would welcome more research about retention rates and work that compares our findings to related online platforms—for example, ride hailing or food delivery platforms.

Third, in this study, we had access to data on U.S. workers only. However, they compete for tasks with 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 platforms and use different skill sets across user groups to identify variations in worker behavior.

A fourth limitation is that we were unable to study *why* the unemployment rate was related to labor supply elasticity. Two mechanisms might have driven 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 other options for individuals, such as the expected return on offline job searches. Alternatively, if unemployment drives particular groups of individuals to such platforms, changes in the demography of online workers account for changes in the online labor supply.[29] Disentangling these different possible mechanisms and user behaviors would be a fruitful ground for further research.

Lastly, our findings suggest a pattern in which low-skilled workers in regions with high unemployment turn to microtasking during normal working hours, which we interpreted as an effort to substitute for income losses related to high unemployment. Although a pattern of unemployed workers using microtasking as a substitute for other work would seem 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 incorporates this additional layer of information and provides additional insights into the underlying mechanisms.

## 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 used data from a large microtasking platform combined with administrative data on unemployment. We applied an identification strategy based on Bartik-type industry shift shares.

[28] Prior 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.

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

We found that high unemployment makes microtasking more attractive to users in regions with an older, predominantly male, white population of workers and a low share of college graduates. This is the opposite of previous findings on high-skilled online labor, and reflects the structural differences between these two forms of online labor. However, the effect on participation was transient and did not affect the number of active incumbent users. At the intensive margin, we found that higher unemployment led to increased microtasking activity during normal working hours, suggesting a pattern of labor substitution. Moreover, the online labor supply became more elastic with an increase in the unemployment rate. Although workers were not very sensitive to wage changes, they reacted more strongly when unemployment rates were high.

Together, our findings highlight that workers started experimenting with microtasking platforms shortly after the Great Recession. We document that microtasking offered an appealing online option for low-skilled 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.

## Acknowledgments

We thank Microworkers.com, especially Nhatvi Nguyen, for giving us data for our analysis. Julia Baumann, Lukas Fortwengel, and Tobias Werner provided outstanding research assistance. We thank participants of the 9th ICT Conference at Télécom ParisTech 2017, the 15th ICT Conference at the ZEW 2017, the Munich Doctoral Workshop on the Economics of Digitization 2017, the Munich Summer Institute 2017, the Workshop on Flexible Work in the Digital Age 2017, ASSA 2018, IIOC 2018, the NBER Summer Institute 2018, and the 2nd IZA/OECD Workshop in Paris. In particular, we thank Maya Bacache, Chiara Belletti, Antonio Cassili, Horst Entorf, Axel Gautier, Avi Goldfarb, John Horton, Maximilan Kasy, Peter Rossi, Prasanna Tambe, Paola Tubaro, Catherine Tucker, Le Wang, Andrea Weber, Rudolf Winter-Ebmer, Krzysztof Wozniak, and Christine Zulehner for helpful comments. We also thank Corey Angst, the associate editor and three anonymous reviewers for helpful comments and suggestions. The authors alone are responsible for the content. This paper contains the opinion of the authors and does not necessarily represent the position of KfW or SCHUFA. This work was supported by the State Government of Baden-Württemberg, Germany, through the research program Strengthening Efficiency and Competitiveness in the European Knowledge Economies (SEEK), the German Research Foundation (DFG) under grants HO4770/2-2 and TR257/38-2 and the French Research Agency (ANR) under grant ANR-19-CE10-0012 (“HUSH”).

## References

Adelino, M., Ma, S., & Robinson, D. (2017). Firm age, investment opportunities, and job creation. *The Journal of Finance*, *72*(3), 999-1038. https://doi.org/10.1111/jofi.12495

Agrawal, A., Catalini, C., & Goldfarb, A. (2015a). Crowdfunding: Geography, social networks, and the timing of investment decisions. *Journal of Economics & Management Strategy*, *24*(2), 253-274. https://doi.org/10.1111/jems.12093

Agrawal, A., Horton, J. J., Lacetera, N., & Lyons, E. (2015b). Digitization and the contract labor market: A research agenda. *Economic Analysis of the Digital Economy*, 219-250. https://doi.org/10.7208/9780226206981-011

Altonji, J. G. & Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In J. M. Abowd & R. B. Freeman (Eds.), *Immigration, trade, and the labor market* (pp. 201-234). University of Chicago Press. https://doi.org/10.3386/w3123

Angrist, J. D. & Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist’s companion*. Princeton University Press. https://doi.org/10.1007/s00362-009-0284-y

Artuc, E., Lederman, D., & Porto, G. (2015). A mapping of labor mobility costs in the developing world. *Journal of International Economics*, *95*(1), 28-41. https://doi.org/10.1016/j.jinteco.2014.10.007

Asatryan, Z., Bittschi, B., & Doerrenberg, P. (2017). Remittances and public finances: Evidence from oil-price shocks. *Journal of Public Economics*, *155*, 122-137. https://doi.org/10.1016/j.jpubeco.2017.09.009

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, *103*(6), 2121-2168. https://doi.org/110.1257/aer.103.6.2121

Autor, D. H. & Duggan, M. G. (2003). The rise in the disability rolls and the decline in unemployment. *The Quarterly Journal of Economics*, *118*(1), 157-206. https://doi.org/10.1162/00335530360535171

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., & Wong, A. (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, *32*(3), 259-280. https://doi.org/10.1257/jep.32.3.259

Balakrishnan, A., Sundaresan, S., & Zhang, B. (2014). Browse-and-switch: Retail-online competition under value uncertainty. *Production and Operations Management*, *23*(7), 1129-1145. https://doi.org/10.1111/poms.12165

Bargain, O., Orsini, K., & Peichl, A. (2014). Comparing labor supply elasticities in Europe and the United States new results. *Journal of Human Resources*, *49*(3), 723-838. https://doi.org/10.3368/jhr.49.3.723

Bartik, T. J. (1991). *Who benefits from state and local economic development policies?* WE Upjohn Institute for Employment Research. https://doi.org/10.17848/9780585223940

Bell, D. R., Gallino, S., & Moreno, A. (2018). Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science*, *64*(4), 1629-1651. https://doi.org/10.1287/mnsc.2016.2684

Berg, J. (2015). Income security in the on-demand economy: Findings and policy lessons from a survey of crowdworkers. *Comparative Labor Law & Policy Journal*, *37*, 543-570.

Berg, J., Furrer, M., Harmon, E., Rani, U., & Silberman, M. S. (2018). Digital labour platforms and the future of work. *Towards* *decent work in the online world. rapport de l'OIT*. Available at http://ilo.ch/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_645337.pdf

Berinsky, A. J., Margolis, M. F., & Sances, M. W. (2014). Separating the shirkers from the workers? Making sure respondents pay attention on self-administered surveys. *American Journal of Political Science*, *58*(3), 739-753. https://doi.org/10.1111/ajps.12081

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, *25*(2), 242-262. https://doi.org/10.2307/2555829

Blanchard, O. & Katz, L. F. (1992). Regional evolutions. *Brooking Papers on Economic Activity*, *23*(1), 1-75.

Bound, J. & Holzer, H. J. (2000). Demand shifts, population adjustments, and labor market outcomes during the 1980s. *Journal of Labor Economics*, *18*(1), 20-54. https://doi.org/10.1086/209949

Brabham, D. C. (2010). Moving the crowd at threadless: Motivations for participation in a crowdsourcing application. *Information, Communication & Society*, *13*(8), 1122-1145. https://doi.org/10.1080/13691181003624090

Brown, D. & De Cao, E. (2018). The impact of unemployment on child maltreatment in the United States (Working paper 2018-04). Institute for Social and Economic Research. Available at http://www.nuff.ox.ac.uk/economics/papers/2017/BrownDeCao_ChildMaltreatmentSEP17.pdf

Brynjolfsson, E., Hu, Y., & Rahman, M. S. (2009). Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science*, *55*(11), 1755- 1765. https://doi.org/10.1287/mnsc.1090.1062

Camerer, C., Babcock, L., Loewenstein, G., & Thaler, R. (1997). Labor supply of New York City cabdrivers: One day at a time. *The Quarterly Journal of Economics*, *112*(2), 407-441. https://doi.org/10.1162/003355397555244

Chan, J., Ghose, A., & Seamans, R. (2016). The internet and racial hate crime: Offline spillovers from online access. *MIS Quarterly*, *40*(2), 381-403. https://doi.org/10.25300/MISQ/2016/40.2.05

Chandler, D. & Kapelner, A. (2013). Breaking monotony with meaning: Motivation in crowdsourcing markets. *Journal of Economic Behavior & Organization, 90,* 123-133. https://doi.org/10.1016/j.jebo.2013.03.003

Chandler, J., Mueller, P., & Paolacci, G. (2014). Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior Research Methods*, *46*(1), 112-130. https://doi.org/10.3758/s13428-013-0365-7

Chandler, J. & Shapiro, D. (2016). Conducting clinical research using crowdsourced convenience samples. *Annual Review of Clinical Psychology, 12,* 53-81. https://doi.org/10.1146/annurev-clinpsy-021815-093623

Chen, M. K., Chevalier, J. A., Rossi, P. E., & Oehlsen, E. (2017). The value of flexible work: Evidence from uber drivers. *Journal of Political Economy, 127*(6), 2735-2794. https://doi.org/10.1086/702171

Chintagunta, P. K., Chu, J., & Cebollada, J. (2012). Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Science*, *31*(1), 96-114. https://doi.org/10.1287/mksc.1110.0678

Cognilytica (2019). *Data engineering, preparation, and labeling for AI 2019* (Technical report).

Crawford, V. P. & Meng, J. (2011). New York City cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. *American Economic Review*, *101*(5), 1912-32. https://doi.org/10.1257/aer.101.5.1912

Cui, T. H., Ghose, A., Halaburda, H., Iyengar, R., Pauwels, K., Sriram, S., Tucker, C., & Venkataraman, S. (2021). Informational challenges in omnichannel marketing: remedies and future research. *Journal of Marketing*, *85*(1), 103-120. https://doi.org/10.1177/0022242920968810

Deng, X., Joshi, K. D., & Galliers, R. D. (2016). The duality of empowerment and marginalization in microtask crowdsourcing: Giving voice to the less powerful through value sensitive design. *MIS Quarterly*, *40*(2), 279-302. https://doi.org/10.25300/MISQ/2016/40.2.01

Deng, X. N. & Joshi, K. D. (2016). Why individuals participate in micro-task crowdsourcing work environment: Revealing crowdworkers' perceptions. *Journal of the Association for Information Systems*, *17*(10), 648-673. https://doi.org/10.17705/1jais.00441

Difallah, D., Filatova, E., & Ipeirotis, P. (2018). Demographics and dynamics of mechanical turk workers. In *Proceedings of the eleventh ACM international conference on web search and data mining* (pp. 135-143). https://doi.org/10.1145/3159652.3159661

Dranove, D., Forman, C., Goldfarb, A., & Greenstein, S. (2014). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy, 6*(4), 239-270. https://doi.org/10.1257/pol.6.4.239

Dube, A., Jacobs, J., Naidu, S., & Suri, S. (2020). Monopsony in online labor markets. *American Economic Review: Insights*, *2*(1), 33-46. https://doi.org/10.1257/aeri.20180150

Dube, A., Manning, A., & Naidu, S. (2018). Monopsony and employer mis-optimization explain why wages bunch at round numbers (Technical report, National Bureau of Economic Research). https://doi.org/10.1086/426040

Farber, H. S. (2005). Is tomorrow another day? The labor supply of New York City cabdrivers. *Journal of Political Economy*, *113*(1), 46-82. https://doi.org/10.1086/426040

Farber, H. S. (2008). Reference-dependent preferences and labor supply: The case of New York City taxi drivers. *American Economic Review*, *98*(3), 1069-1082. https://doi.org/10.1257/aer.98.3.1069

Farber, H. S. (2015). Why you can't find a taxi in the rain and other labor supply lessons from cab drivers. *The Quarterly Journal of Economics*, *130*(4), 1975-2026. https://doi.org/10.1093/qje/qjv026

Farrell, D. & Greig, F. (2016). *Paychecks, paydays, and the online platform economy: Big data on income volatility*. JP Morgan Chase Institute. Available at https://doi.org/10.2139/ssrn.2911194

Fehr, E. & Goette, L. (2007). Do workers work more if wages are high? Evidence from a randomized field experiment. *American Economic Review*, *97*(1), 298-317. https://doi.org/10.1257/aer.97.1.298

Filippas, A., Horton, J. J., & Golden, J. (2018). Reputation inflation. In *Proceedings of the 2018 ACM Conference on Economics and Computation* (pp. 483-484). https://doi.org/10.1145/3219166.3219222

Forman, C., Ghose, A., & Goldfarb, A. (2009). Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Science*, *55*(1), 47-57. https://doi.org/10.1287/mnsc.1080.0932

Fougère, D., Kramarz, F., & Pouget, J. (2009). Youth unemployment and crime in France. *Journal of the European Economic Association*, *7*(5), 909-938. https://doi.org/10.1162/JEEA.2009.7.5.909

Frei, B. (2009). *Paid crowdsourcing: Current state & progress toward mainstream business use.* (Smartsheet white paper). Available at https://www.scribd.com/document/137419272/Paid-Crowdsourcing

Gadiraju, U., Checco, A., Gupta, N., & Demartini, G. (2017). Modus operandi of crowd workers: The invisible role of microtask work environments. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. https://doi.org/10.1145/3130914

Gallino, S. & Moreno, A. (2014). Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science*, *60*(6), 1434-1451. https://doi.org/10.1287/mnsc.2014.1951

Gefen, D. & Carmel, E. (2008). Is the world really flat? A look at offshoring at an online programming marketplace. *MIS Quarterly*, *32*(2), 367-384. https://doi.org/10.2307/25148844

Ghose, A., Goldfarb, A., & Han, S. P. (2013). How is the mobile internet different? Search costs and local activities. *Information Systems Research*, *24*(3), 613-631. https://doi.org/10.1287/isre.1120.0453

Goldfarb, A. & Tucker, C. (2011). Search engine advertising: Channel substitution when pricing ads to context. *Management Science*, *57*(3), 458-470. https://doi.org/10.1287/mnsc.1100.1287

Goldfarb, A. & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, *57*(1), 3-43. https://doi.org/10.1257/jel.20171452

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586-2624. https://doi.org/10.1257/aer.20181047

Gould, E. D., Weinberg, B. A., & Mustard, D. B. (2002). Crime rates and local labor market opportunities in the United States: 1979-1997. *Review of Economics and Statistics*, *84*(1), 45-61. https://doi.org/10.1162/003465302317331919

Hagedorn, M., Karahan, F., Manovskii, I., & Mitman, K. (2013). *Unemployment benefits and unemployment in the Great Recession: The role of macro effects* (Technical report, National Bureau of Economic Research). https://doi.org/10.3386/w19499

Hirth, M. (2016). *Modeling crowdsourcing platforms: A use-case driven approach* [Ph.D. dissertation]. Julius-Maximilians-Universität Würzburg. Available at https://d-nb.info/1120306043/34

Hirth, M., Hossfeld, T., & Tran-Gia, P. (2011). Anatomy of a crowdsourcing platform: Using the example of microworkers.com. In *Proceedings of the 2011 Fifth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing* (pp. 322-329). https://doi.org/10.1109/IMIS.2011.89

Horton, J. J. (2010). Online labor markets. In *Proceedings of the International Workshop on Internet and Network Economics* (pp. 515-522). Springer. https://doi.org/10.1007/978-3-642-17572-5_45

Horton, J. J. & Chilton, L. B. (2010). The labor economics of paid crowdsourcing. In *Proceedings of the 11th ACM Conference on Electronic Commerce* (pp. 209-218). https://doi.org/10.1145/1807342.1807376

Horton, J. J., Rand, D. G., & Zeckhauser, R. J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental economics*, *14*(3), 399-425. https://doi.org/10.1007/s10683-011-9273-9

Huang, N., Burtch, G., Hong, Y., & Pavlou, P. A. (2020). Unemployment and worker participation in the gig economy: Evidence from an online labor market. *Information Systems Research*, *31*(2), 431-448. https://doi.org/10.1287/isre.2019.0896

Ipeirotis, P. G. (2010). *Demographics of Mechanical Turk* (NYU working paper, CEDER-10-01). Available at https://ssrn.com/abstract=1585030

Jiang, L., Wagner, C., & Chen, X. (2021). Taking time into account: Understanding microworkers' continued participation in microtasks. *Journal of the Association for Information Systems*, *22*(4), 893-930. https://doi.org/10.17705/1jais.00684

Jing, B. (2018). Showrooming and webrooming: Information externalities between online and offline sellers. *Marketing Science*, *37*(3), 469-483. https://doi.org/10.1287/mksc.2018.1084

Kaganer, E., Carmel, E., Hirschheim, R., & Olsen, T. (2013). Managing the human cloud. *MIT Sloan Management Review*, *54*(2). https://sloanreview.mit.edu/article/managing-the-human-cloud/

Katz, L. F. & Krueger, A. B. (2017). The role of unemployment in the rise in alternative work arrangements. *American Economic Review*, *107*(5), 388-92. https://doi.org/10.1257/aer.p20171092

Kaufmann, N., Schulze, T., & Veit, D. (2011). More than fun and money. Worker motivation in crowdsourcing: A study on Mechanical Turk. In *Proceedings of the Americas Conference on Information Systems*. https://aisel.aisnet.org/amcis2011_submissions/340

Keskinen, P., Winschiers-Theophilus, H., Chivuno-Kuria, S., Müller, A., & Nieminen, M. (2021). Digital microwork as a livelihood strategy in a Namibian informal settlement. *The Electronic Journal of Information Systems in Developing Countries*, *88*(1), Article e12197. https://doi.org/10.1002/isd2.12197

Kokkodis, M. (2021). Dynamic, multidimensional, and skillset-specific reputation systems for online work. *Information Systems Research*, *32*(3),688-712 https://doi.org/10.1287/isre.2020.0972

Kokkodis, M. & Ipeirotis, P. G. (2016). Reputation transferability in online labor markets. *Management Science*, *62*(6), 1687-1706. https://doi.org/10.1287/mnsc.2015.2217

Kost, D., Fieseler, C., & Wong, S. I. (2018). Finding meaning in a hopeless place? The construction of meaningfulness in digital microwork. *Computers in Human Behavior*, *82*, 101-110. https://doi.org/10.1016/j.chb.2018.01.002

Kroft, K. & Notowidigdo, M. J. (2016). Should unemployment insurance vary with the unemployment rate? theory and evidence. *The Review of Economic Studies*, *83*(3), 1092-1124. https://doi.org/10.1093/restud/rdw009

Kuek, S. C., Paradi-Guilford, C., Fayomi, T., Imaizumi, S., Ipeirotis, P., Pina, P., & Singh, M. (2015). *The global opportunity in online outsourcing*. The World Bank, Washington. Available at https://econpapers.repec.org/RePEc:wbk:wboper:22284

Kuziemko, I., Norton, M. I., Saez, E., & Stantcheva, S. (2015). How elastic are preferences for redistribution? Evidence from randomized survey experiments. *American Economic Review*, *105*(4), 1478-1508. https://doi.org/10.1257/aer.20130360

Kässi, O. & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological*

*Forecasting and Social Change*, *137*, 241-248. https://doi.org/10.1016/j.techfore.2018.07.056

Lin, M. & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, *62*(5), 1393-1414. https://doi.org/10.1287/mnsc.2015.2206

Luo, X. & Zhang, J. (2013). How do consumer buzz and traffic in social media marketing predict the value of the firm? *Journal of Management Information Systems*, *30*(2), 213-238. https://doi.org/10.2753/mis0742-1222300208

Martin, D., Carpendale, S., Gupta, N., Hoßfeld, T., Naderi, B., Redi, J., Siahaan, E., & Wechsung, I. (2017). Understanding the crowd: Ethical and practical matters in the academic use of crowdsourcing. In *Evaluation in the crowd.: Crowdsourcing and human-centered experiments* (pp. 27-69). Springer. https://doi.org/10.1007/978-3-319-66435-4_3

Mehra, A., Kumar, S., & Raju, J. S. (2018). Competitive strategies for brick-and-mortar stores to counter "showrooming". *Management Science*, *64*(7), 3076-3090. https://doi.org/10.1287/mnsc.2017.2764

Mourelatos, E., Giannakopoulos, N., & Tzagarakis, M. (2020). Personality traits and performance in online labour markets. *Behaviour & Information Technology*, *41*(3), 468-484. https://doi.org/10.1080/0144929x.2020.1815840

Müller, K. & Schwarz, C. (2020). *From hashtag to hate crime: Twitter and anti-minority sentiment.* Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3149103

Niebuhr, A., Granato, N., Haas, A., & Hamann, S. (2012). Does labour mobility reduce disparities between regional labour markets in Germany? *Regional Studies*, *46*(7), 841-858. https://doi.org/10.1080/00343404.2010.532118

Nunn, N. & Qian, N. (2014). US food aid and civil conflict. *American Economic Review*, *104*(6), 1630-66. https://doi.org/10.1257/aer.104.6.1630

Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision making*, *5*(5), 411-419. http://journal.sjdm.org/10/10630a/jdm10630a.pdf

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153-163. https://doi.org/10.1016/j.jesp.2017.01.006

Peer, E., Vosgerau, J., & Acquisti, A. (2014). Reputation as a sufficient condition for data quality on Amazon Mechanical Turk. *Behavior Research Methods*, *46*(4), 1023-1031. https://doi.org/10.3758/s13428-013-0434-y

Rani, U. & Furrer, M. (2019). On-demand digital economy: Can experience ensure work and income security for Microtask workers? *Jahrbücher für Nationalökonomie und Statistik*, *239*(3), 565-597. https://doi.org/10.1515/jbnst-2018-0019

Ross, J., Irani, L., Silberman, M., Zaldivar, A., & Tomlinson, B. (2010). Who are the crowdworkers? Shifting demographics in Mechanical Turk. In *CHI'10 extended abstracts on human factors in computing systems* (pp. 2863-2872). https://doi.org/10.1145/1753846.1753873

Rossi, P. E. (2014). Even the rich can make themselves poor: A critical examination of iv methods in marketing applications. *Marketing Science*, *33*(5), 655-672. https://doi.org/10.1287/mksc.2014.0860

Rossotto, C. M., Kuek, S. C., & Paradi-Guilford, C. (2012). *New frontiers and opportunities in work: ICT is dramatically reshaping the global job market.* (Information and Communication Technologies (ICT) policy notes series, no. 3) World Bank Group. http://documents.worldbank.org/curated/en/195551468331035511/New-frontiers-and-opportunities-in-work-ICT-is-dramatically-reshaping-the-global-job-market

Rouse, S. V. (2015). A reliability analysis of mechanical Turk data. *Computers in Human Behavior*, *43*, 304-307. https://doi.org/10.1016/j.chb.2014.11.004

Schnitzer, S., Rensing, C., Schmidt, S., Borchert, K., Hirth, M., & Tran-Gia, P. (2015). Demands on task recommendation in crowdsourcing platforms-the worker's perspective. In *Proceedings of the ACM RecSys 2015 CrowdRec Workshop*. Available at https://www.kom.tu-darmstadt.de/papers/SRS+15.pdf

Seamans, R. & Zhu, F. (2014). Responses to entry in multi-sided markets: The impact of craigslist on local newspapers. *Management Science*, *60*(2), 476-493. https://doi.org/10.1287/mnsc.2013.1785

Steelman, Z. R., Hammer, B. I., & Limayem, M. (2014). Data collection in the digital age. *MIS Quarterly*, *38*(2), 355-378. https://doi.org/10.25300/misq/2014/38.2.02

Stock, J. & Yogo, M. (2005). *Asymptotic distributions of instrumental variables statistics with many instruments*. In D. W. K. Andrews & J. H. Stock (Eds.) *Essays in honor of Thomas Rothenberg* (pp. 109-120). Cambridge University Press. https://doi.org/10.1017/cbo9780511614491.007

Stuart, M., Joyce, S., Carson, C., Trappmann, V., Umney, C., Forde, C., Oliver, L., Valizade, D., Hardy, K., Alberti, G., et al. (2017). *The social protection of workers in the platform economy* (Technical report). https://doi.org/10.1108/s0742-61862019 0000025009

Teodoro, R., Ozturk, P., Naaman, M., Mason, W., & Lindqvist, J. (2014). The motivations and experiences of the on-demand mobile workforce. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 236-247). https://doi.org/10.1145/2531602.2531680

Tolbert, C. M. & Sizer, M. (1996). *U.S. commuting zones and labor market areas a 1990 update.* (ERS staff paper, 9614). Available at https://ideas.repec.org/p/ags/uerssr/278812.html

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003

Wang, K. & Goldfarb, A. (2017). Can offline stores drive online sales? *Journal of Marketing Research*, *54*(5), 706-719. https://doi.org/10.1509/jmr.14.0518

Xu, J., Forman, C., Kim, J. B., & Van Ittersum, K. (2014). News media channels: Complements or substitutes? Evidence from mobile phone usage. *Journal of Marketing*, *78*(4), 97-112. https://doi.org/10.1509/jm.13.0198

Xu, K., Chan, J., Ghose, A., & Han, S. P. (2017). Battle of the channels: The impact of tablets on digital commerce. *Management Science*, *63*(5), 1469-1492. https://doi.org/10.1287/mnsc.2015.2406

Xue, M., Hitt, L. M., & Chen, P.-y. (2011). Determinants and outcomes of internet banking adoption. *Management Science*, *57*(2), 291-307. https://doi.org/10.1287/mnsc.1100.1187

Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research*, *54*(5), 687-705. https://doi.org/10.1509%2Fjmr.15.0204

## About the Authors

**Ulrich Laitenberger** is an associate professor at Tilburg University. He is also a research associate at Centre for European Economic Research (ZEW), Germany and CESIfo network affiliate. He is a member of the expert group of the EU Observatory on the Online Platform Economy of the European Commission. He obtained his Ph.D. in business economics at KU Leuven in November 2015, and his *Habilitation* to direct research (HDR) in October 2019. His research focuses on strategies and the regulation of digital platforms. His work has been published in journals like *American Economic Journal: Microeconomics, Marketing Science,* and *Quantitative Marketing and Economics.* https://orcid.org/0000-0002-7009-0190

**Steffen Viete** is an economist at KfW Research. Previously he worked for the German Council of Economic Experts and in the Digital Economy Research Department at ZEW. His research spans several topics, with a particular focus on the interactions of technology, productivity, innovation, entrepreneurship, and business dynamism. He holds a Ph.D. in economics from Goethe University Frankfurt. https://orcid.org/0000-0002-0742-8646

**Olga Slivko** is an assistant professor in the Department of Technology and Operations Management at Rotterdam School of Management (RSM), Erasmus University. Prior to that, she worked as a postdoctoral researcher in digital economy at ZEW, Germany. She conducts research in the field of digital economy and information systems, focusing on the economic and societal impact of UGC and investigating how platform governance mechanisms and policy regulations affect UGC communities. Her research has been published in journals such as *Information Systems Research, Journal of Economics and Management Strategy,* and *Experimental Economics.* She holds a Ph.D. in economics from University Rovira I Virgili (Spain). https://orcid.org/0000-0001-6062-2870

**Michael Kummer** has been an assistant professor at the University of East Anglia (UEA) in Norwich, UK, since August 2018. Prior to that, he had been an assistant professor in the School of Economics of the Georgia Institute of Technology in Atlanta, USA, since 2015. His research interests focus on the generation of user-generated content in networks, the structure of online markets, and the interaction of firms and consumers on price comparison websites. He has published in scientific journals such as *Management Science, Information Systems Research, Journal of Economics and Management Strategy,* and *Econometric Journal.* https://orcid.org/0000-0002-5661-7208

**Kathrin Borchert** is a data analyst at SCHUFA Holding AG, Germany. Her research focuses on multiple aspects of crowdworking, such as the impact of task design on the quality of working results and the investigation of users' quality of experience in thin-client architectures as deployed in business infrastructures. She holds a Ph.D. in computer science from the University of Würzburg, Germany.

**Matthias Hirth** is a junior professor in the Department of Electrical Engineering and Information Technology, TU Ilmenau, and heads the User-Centered Analysis of Multimedia Data Group. He conducts research on the collection and modeling of the subjective user perception (quality of experience–- QoE) of media data and technical systems, the user-centered optimization of the technical systems, and the optimization and application of crowdsourcing-based systems. His research has been published in journals such as *EEE Transactions on Multimedia, Springer Quality and User Experience,* and *SAGE Social Science Computer Review*. He holds a Ph.D. in computer science from the University of Würzburg, Germany, where he worked previously as a research fellow in the Chair of Communication Networks. https://orcid.org/0000-0002-1359-363X

# Appendix 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***<br>(0.508) | 1.671*<br>(0.896) | | |
| Bartik shock | | | -0.059***<br>(0.011) | -0.052***<br>(0.012) |
| Offline wage | -0.054***<br>(0.010) | -0.022<br>(0.014) | -0.001*<br>(0.000) | -0.001**<br>(0.000) |
| % age 15-24 (i) | -6.563***<br>(1.558) | 0.274<br>(3.132) | 0.068<br>(0.067) | -0.006<br>(0.071) |
| % age 45-64 (i) | -0.161<br>(1.726) | 4.467<br>(3.990) | -0.200***<br>(0.075) | -0.155<br>(0.094) |
| % male (i) | -4.215<br>(4.170) | -13.393<br>(10.561) | 0.932***<br>(0.221) | 1.549***<br>(0.240) |
| % white (i) | 4.336*<br>(2.339) | -13.004**<br>(5.146) | -0.482***<br>(0.110) | -0.418***<br>(0.112) |
| Year quarter FE | Yes | Yes | Yes | Yes |
| Commuting zone FE | Yes | Yes | Yes | Yes |
| Observations | 13140 | 10950 | 13140 | 10945 |

**Note**: The table shows the OLS results (Columns 1 and 2) and the first stage (Columns 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (i) indicates that data were only available yearly and were therefore linearly interpolated to the quarter level.

### *Rotemberg Weights*

We computed 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 found 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 50% (0.635/1.208=.526) of the positive weight in the estimator.[30] 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 compared 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.

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 ($\alpha_k$). 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 relied 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).[31]

### *Plausibility of the Identifying Assumption*

[30] Compare the sum of $\alpha_k$ in Panel D with the sum of positive weights reported in Panel A.
[31] See Goldsmith-Pinkham et al. (2020, p. 2598).

While the identifying assumptions cannot be tested directly, we checked their plausibility in different ways. We note first that in our setting there was no pre-period and so it was not possible to test for parallel pre-trends without further assumptions. Second, we tested 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% of the variation in the share of the "oil and gas extraction" via our covariates. Second, we found that some of our top 5 industries are statistically significantly correlated with the share of older and male population.

## Overidentification and Heterogeneity

We followed Goldsmith-Pinkham et al. (2020) and implemented alternative estimators which allowed testing 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 exogenous. 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 5) 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 $\beta_l$) 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 βk among the negative weight industries is very different than the mean of the $\beta_k$ among the industries with positive weights.

**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*** | | | | | |
| | $\boldsymbol{\alpha_k}$ | $\boldsymbol{g_k}$ | $\boldsymbol{\beta_k}$ | $\boldsymbol{F_k}$ | $\boldsymbol{Var(z_k)}$ |
| $\alpha_k$ | 1 | | | | |
| $g_k$ | -0.009 | 1 | | | |
| $\beta_k$ | -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 $\alpha_k$*** | | | | | |
| | **Sum** | **Mean** | | | |
| 2011 | .141 | .0001 | | | |
| 2012 | .179 | .0001 | | | |
| 2013 | .163 | .0001 | | | |
| 2014 | .158 | .0001 | | | |
| 2015 | .360 | .0003 | | | |
| ***Panel D: Top 5 Rotemberg weight industries*** | | | | | |
| | $\boldsymbol{\hat{\alpha}_k}$ | $\boldsymbol{g_k}$ | $\boldsymbol{\hat{\beta}_k}$ | **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 $\boldsymbol{\beta_k}$ for positive and negative weights*** | | | | | |
| | **$\boldsymbol{\alpha}$-weighted sum** | **Share of overall $\boldsymbol{\beta}$** | **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 (αk), the national component of growth ($g_k$), the just-identified coefficient estimates (βk), 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% 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 βk vary with the positive and negative Rotemberg weights.

**Table A3. Relationship between Industry Shares and Characteristics**

| Industry Code | 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's | -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 |

**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. *t*-statistics in parentheses. $* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$. (i) indicates that data were only available yearly and were therefore linearly interpolated to the quarter level.

**Table A4. OLS and IV Estimates**

| | Unemployment 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 commuting zone 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 zone, 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.

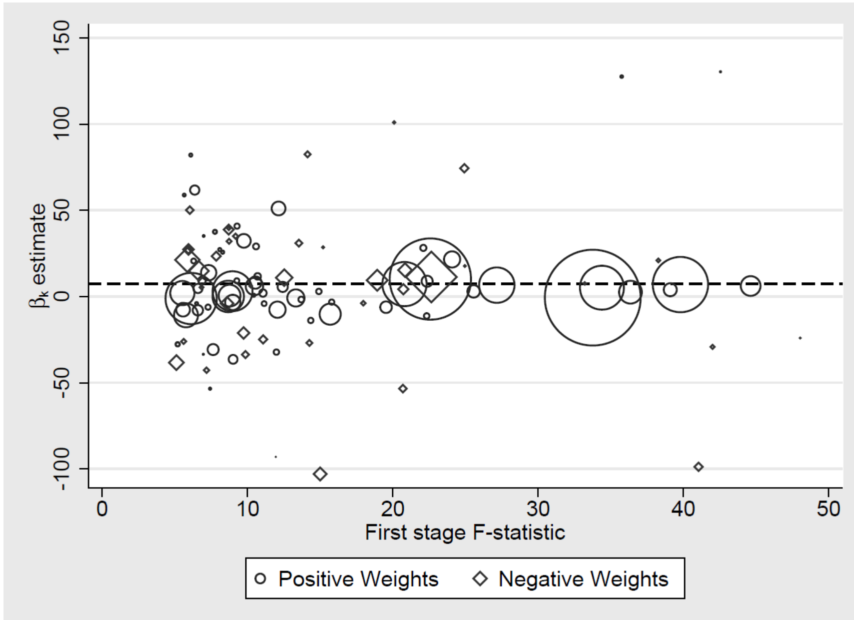



**Figure A1. Heterogeneity of $\beta_k$**

**Note**: Figure A1 plots the relationship between each instruments' $\beta_k$, first-stage *F*-statistics and the Rotemberg weights. Each point is a separate instrument's estimates (industry share). The figure plots the estimated βk for each instrument on the *y*-axis and the estimated first stage *F*-statistic on the *x*-axis. The size of the points is 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 βhat 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.

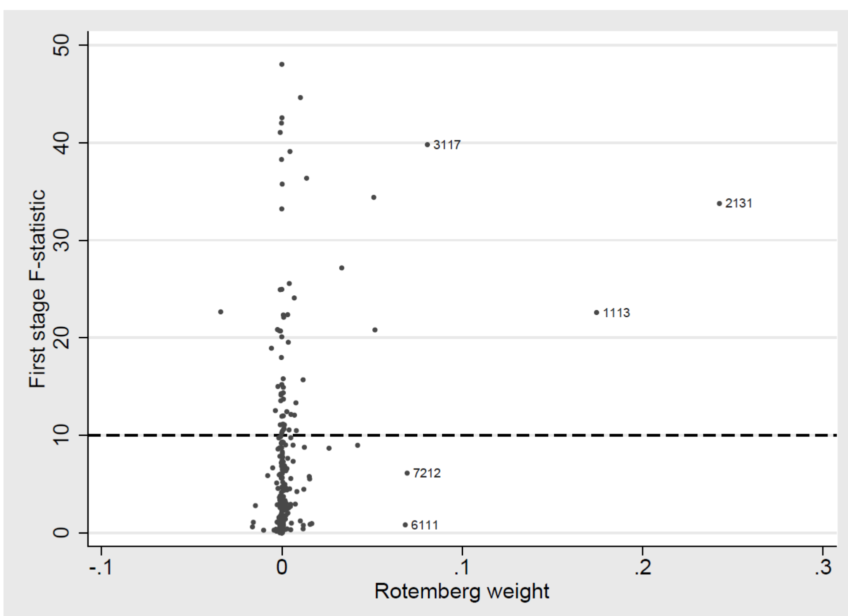



**Figure A2. First-stage vs. Rotemberg weights**

**Note**: Figure A2 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 the approach in the data section. The labeled 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.

# Appendix B

## Full Hourly Decomposition

**Table B1. Volume of Tasks by Hour of the Day, Only Weekdays**

| Variable | Coefficient | *SE* | Variable | Coefficient | *SE* |
|---|---|---|---|---|---|
| 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 | | Commuting zone FE | Yes | |
| $R^2$ within | 0.41 | | Year-quarter FE | Yes | |
| Observations | 358794 | | Task complexity | Yes | |

**Note**: The table shows regressions of the effect of 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 weekdays. Standard errors in parentheses are clustered by commuting zone and are robust to heteroscedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.