Skill-Biased Technical Change Again? Estimating the Effect of TaskRabbit on Local Employment in the Housekeeping Industry

Short Paper

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Abstract

The rise of gig platforms brings new opportunities and challenges to local labor markets: they may complement offline workers by facilitating service matching and creating jobs for them, or they may substitute offline workers by intensifying the competition among them. Drawing on Skill-Biased Technical Change and digital platforms theory, we study the impacts of gig platforms on local employment in the housekeeping industry. Exploiting the staggered expansion pattern of TaskRabbit (a gig platform that matches freelance labor to local demand for everyday tasks) into US counties at different times, we identify its impact on the housekeeping industry. Our difference-in-differences estimate shows a disproportionate decrease in full-time housekeeping employment in TaskRabbit-operated areas. The decline is mainly driven by cognitive (middle-skilled) workers (i.e., managers) instead of manual (low-skilled) workers (i.e., janitors). Additional evidence, however, implies that gig platforms may not crowd out workers but rather they incubate local entrepreneurship through additional self-employment. Implications for platform design, policy, and research are discussed.

Keywords: Gig Platforms, Labor, Skills, Technical Change, Difference-in-Differences

Introduction

The rise of gig platforms (e.g., Uber, TaskRabbit) has facilitated the shift from permanent to on-demand employment and matching of labor to employers from offline to online settings (Kuhn 2016). Gig platforms connect service providers directly with customers in a seamless manner via the Internet or mobile apps (Zervas et al. 2015, Fang et al. 2016). The popular press and academic research have offered two hitherto countervailing predictions on the impact of gig platforms on offline labor markets. One prediction argues that gig platforms enhance flexibility, fluidity, and innovation, which stimulate employment and wage equality (e.g., Fraiberger and Sundararajan 2017). The competing prediction argues that gig platforms intensify competition among workers, which reduces their surplus and wages (e.g., Schor 2017).

Accordingly, it remains unclear about what is the impact of gig platforms on offline labor markets; Specifically, how do gig platforms affect the number of full-time local workers in the same offline industry? To answer this question, we theorize and examine the effect of a major online housekeeping gig platform (TaskRabbit) on the offline housekeeping industry. While extant research in online labor markets mainly focuses on offshoring information-based virtual jobs on global online platforms (e.g., Freelancer, Upwork)
Our research context is thus about housekeeping service (e.g., janitors, cleaners), a major service provided by gig platform TaskRabbit. TaskRabbit is the earliest and largest gig platform in the United States that matches freelancers with local housekeeping demand, such as housekeeping, cleaning, and moving. This gig platform differs from traditional offline housekeeping businesses in two aspects. First, TaskRabbit has a distinct matching mechanism. Gig platforms directly match labor supply and demand online based on the buyers’ requirements and the service providers’ qualifications, which reduces search cost and improves matching efficiency. The automated matching may reduce the demand for cognitive (or middle-skilled) workers (e.g., first-line supervisors and managers) whose primary task is to schedule service (Bekman 1998). We build on Skill-Biased Technical Change (STBCT) theory (Autor et al. 2003, Card 2001) to argue that the effects of gig platforms are heterogeneous across workers with distinct skills—cognitive (or middle-skilled) (e.g., first-line managers) and manual (or low-skilled) (e.g., janitors) (Autor et al. 2003) (Table 1) in the offline housekeeping industry. Specifically, gig platforms that function as matchmakers may replace or even eliminate cognitive workers whose primary task is to schedule housekeeping services.

To answer these questions, we first theorize the role of gig platforms in local labor markets. Drawing upon platform theory (e.g., Brynjolfsson and Smith 2000), we propose two competing theoretical predictions. On the one hand, the introduction of gig platforms may increase the number of workers in offline labor markets because they substitute skilled workers (Bekman 1998). We build on Skill-Biased Technical Change (STBCT) theory (Autor et al. 2003, Card 2001) to argue that the effects of gig platforms are heterogeneous across workers with distinct skills—cognitive (or middle-skilled) (e.g., first-line managers) and manual (or low-skilled) (e.g., janitors) (Autor et al. 2003) (Table 1) in the offline housekeeping industry. Specifically, gig platforms that function as matchmakers may replace or even eliminate cognitive workers whose primary task is to schedule housekeeping services.

To empirically examine the above theoretical arguments, we consolidate a unique longitudinal dataset of local (offline) employment in the housekeeping industry in the United States. The dataset covers occupational information at the county level for 10 consecutive years between 2006-2015. We exploit the quasi-experimental setting in which TaskRabbit has been gradually expanded to US counties since 2008, and we use a Difference-in-Differences (DID) approach with county and year fixed effects, as well as county-specific time trends, to exploit the temporal and geographical variations in the introduction of TaskRabbit.

Econometrics analyses yield notable findings. We observe a disproportionate decrease in the local housekeeping employment in the counties where TaskRabbit offers its services. We find that such an effect does vary across workers with different skills. Interestingly, the introduction of TaskRabbit is significantly associated with a decrease in the number of cognitive workers (e.g., managers and supervisors), while the effect is not significant for manual workers. The findings imply that gig platforms do not replace manual workers, but they may substitute middle-skilled cognitive workers in the offline housekeeping industry.

We further explore the underlying mechanisms of labor redistribution. We observe a significant surge in self-employment in the housekeeping industry that follows the introduction of TaskRabbit, with the unemployment rate being constant. These findings, while need further corroboration, may suggest that gig platforms do not eliminate offline workers but boost local entrepreneurship activities in the same industry.

Our study makes important theoretical contributions. First, our study contributes to the literature on the broader impact of the gig economy (e.g., Greenwood and Wattal 2017, Zervas et al. 2015). In response to the debate on the pros and cons of these gig platforms on incumbent employment (Sundararajan 2016), this study offers theoretical arguments and empirical evidence that gig platforms reduce employment in offline labor markets. Second, we theorize the role of different skills and show evidence that the effects of gig platform are driven by the decrease in cognitive workers (e.g., first-line managers and supervisors). Third, this study extends the SBTC literature (e.g., Autor and Dorn 2013, Bresnahan et al. 2002) to the study of online gig platforms; while prior research has mainly documented the role of computerization in
Gig Platforms and Local Labor Markets

the labor market (Card and DiNardo 2002), we focus on gig platforms that match labor demand and supply online and study whether they bring a new form of skill-biased technical change to traditional employment.

This study also provides insightful managerial and policy implications. For service providers, they can search for jobs on gig platforms to maximize matching efficiency. We show evidence that the introduction of a gig platform does not reduce the total number of manual workers, but it creates work flexibility and self-employed activities. For the platform owners or developers, our findings provide insights into how to provide better services. The gig platform could design and personalize features (e.g., matching algorithms) to attract workers at different skill levels. For policymakers, we provide insights into the role of gig platforms in the local labor markets. In response to the heated debate on the societal value of gig platforms, such as TaskRabbit, we show suggestive evidence that these platforms stimulate entrepreneurship activities instead of eliminating workers, implying the need for caution while evaluating and regulating such gig platforms.

Related Literature

Our study draws upon two streams of literature: (i) two-sided matching platforms and, (ii) technical change, skills, and labor (SBTC theory). First, compared with traditional labor markets, these platforms facilitate the exchange of labor and services by reducing search costs (e.g., Freund and Weinhold 2002). Workers and employers can better find each other by searching and browsing tools provided by the platform, which can increase both labor demand and supply (Horton 2010, Acemoglu and Autor, 2011). Second, these platforms utilize user-generated reviews and reputation to reduce moral hazard and enhance users' trust, which increase matching quality and efficiency (Dellarocas and Wood 2008). Third, these platforms provide higher work flexibility by focusing on recurring short-term service (Burtch et al. 2017, Fang et al. 2016). Statistics show that such contingent (gig) jobs are growing fast—a 6% increase in the United States, 7.5% in Europe, and 14% in the United Kingdom in 2016 (Kässi and Lehdonvirta 2016). Thus, on-demand gig jobs have the potential to benefit both workers and the economy as a whole and help to support job growth and household incomes. For instance, Hall and Krueger (2015) find that the main reasons people choose to work for Uber are due to the nature of the work, the flexibility, and the compensation that appeal to them. Our study contributes to this literature by assessing the impact of two-sided matching platforms on offline labor markets in the housekeeping industry.

The second stream of literature our study relates to is focusing on the impact of technological development on wage inequality and employment level. Early as of the 19th century, researchers undertook the investigation of automation on the labor market. When the "Technology Revolution" takes a form of automation, studies (e.g., Marglin 1974, Adler 1988) demonstrated that technical changes reduce the need for skilled workers by making the job easier. Then, as the extensive adoption and application of computing technologies across many industries, the SBTC (“Skill-Biased Technical Change”) hypothesis became dominant in the labor economics literature, that is, technology is biased towards skilled and educated workers by increasing their relative productivity (Acemoglu and Autor 2011). In other words, technology shifts the labor demand towards high-skilled workers by discriminating the low-skilled ones, exacerbating the wage inequality (Acemoglu 2002). As an update of SBTC theory, Autor and Dorn’s (2013) demonstrates that the growth of the high-skill and low-skill jobs and their wages are at the expense of those of middle-skilled workers, who are doing routine work and being easily replaced by technological development. In sum, this stream of literature believes that technical change is skill-biased, which supports the opinion that online gig-economy platform may reduce employment. Our study contributes to this line of work by examining the impact of this new form of IT—online gig-economy platforms—on employment by different skill levels.

Research Context

We study the effect of TaskRabbit on the employment (e.g., the number of workers) in the housekeeping industry. We choose this industry for the following reasons: First, the housekeeping industry offers services (e.g., cleaning) for which labor demand and supply can be matched online via gig platforms. In addition, such an industry is the focus of many large gig platforms (e.g., TaskRabbit, Handy). Second, the housekeeping industry consists of workers with different skill-levels, including both low-skilled (manual) workers, i.e., cleaners and janitors, and middle-skilled (cognitive) workers, i.e., first-line managers and supervisors. Third, the tasks are required to perform locally in offline settings (e.g., an apartment).
Table 1. Jobs with Different Skills in the Housekeeping Industry

<table>
<thead>
<tr>
<th></th>
<th>Definition</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive (Middle-Skilled)</td>
<td>A well-defined set of cognitive tasks that can be executed by machines programmed with explicitly rules.</td>
<td>First-line supervisors and managers</td>
</tr>
<tr>
<td>Manual (Low-Skilled)</td>
<td>A well-defined set of manual tasks that require complex problem-solving and communication activities.</td>
<td>Janitors and cleaners</td>
</tr>
</tbody>
</table>

Notes: Definitions adapted fromAutor et al. (2003).

TaskRabbit is a gig platform that matches freelance labor with local housekeeping demand online, allowing participants to find immediate help in the neighborhood with everyday tasks, such as cleaning and moving (Isaac 2015). Our research focuses on the traditional housekeeping industry where the main services can be covered by TaskRabbit’s business. We choose this platform for three reasons: first, the entry of TaskRabbit has temporal and geographical differences—the company has expanded its services to 20 US counties from 2008 to 2014. The expanding history offers us a good opportunity to utilize DID to identify its impact on local employment. Second, TaskRabbit is one of the earliest and largest gig platforms that allow users to outsource small tasks (e.g., cleaning) to local workers (Isaac 2015). Thus, TaskRabbit is a representative gig platform that potentially has a large influence on the housekeeping industry. Third, while the platform matches housekeeping demand and supply online, it only allows workers to perform their offline services locally within a county. This precludes the concern about geographical interference and allows us to clearly capture the changes in local employment by the introduction of TaskRabbit. Lastly, the housekeeping industry consists of both cognitive (or middle-skilled) and manual (or low-skilled) workers, which provides us a good opportunity to examine the effects of gig platforms on the number of workers with different skills.

Data and Method

To empirically identify the effect of TaskRabbit, we have consolidated a unique longitudinal dataset by integrating data from multiple sources. For independent variables, we collect the data about the entry timing of TaskRabbit to each city in the US through TaskRabbit websites and news. Then, we match each specific city with the corresponding county (or countries). For dependent variables, we collect data from the Bureau of Labor Statistics, which contains detailed information about the number of workers in the local housekeeping industry. To account for local market heterogeneity, following Autor and Dorn (2003), we gather information including population, poverty, education, GDP per capita at the county-year level from the Census Bureau. The definitions of these variables are shown in Table 2.

We employ a DID (difference-in-differences) framework to estimate the changes in the local housekeeping employment (i.e., the number of full-time workers) before and after the introduction of TaskRabbit, compared to that in the remaining counties that have yet been served by TaskRabbit over the same period between 2006-2015. Our unit of analysis is on the county-year basis. The specification is as follows:

\[
y_{it} = \beta_1 TaskRabbit_{it} + X'_{it}\beta_2 + y_i + \lambda_t + \theta_i t + \epsilon_{it} \tag{Eq. 1}
\]

Where \(y_{it}\) represents the log-transformed number of full-time workers in county \(i\) in year \(t\). The independent variable is a dichotomous indicator, \(TaskRabbit_{it}\), about whether the TaskRabbit platform entered county \(i\) in year \(t\). We include a vector of covariates, \(X\), to account for time-varying county-level heterogeneity from four perspectives. First, we control aggregated education attainment for each county. Second, we account for the demographic and social-economic development of each county, including total population, the ratio of population that aged above 65 years, the ratio of female in population, Caucasian percentage, poverty percentage. Third, we control for service and high technology occupations share in the total employment to account for employment differences in the related industry among counties. To account for the time-invariant unobserved heterogeneities, we use time fixed effects (\(\lambda_t\)) to account for common trends of labor supply and demand in the U.S., and as well as county fixed effects (\(y_i\)) for unobserved time-invariant heterogeneity (e.g., geographical location, climates) in each county. Specifically, we include county-specific linear time trends (\(\theta_i t\)) to allow for varying trajectories in employment patterns across counties, which capture the overall demand changes across counties.
Table 2. Main Variables and Data Sources

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
<th>Data Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>TaskRabbitEntry</td>
<td>=1 if TaskRabbit serves the ith county in tth year, otherwise 0</td>
<td>News &amp; Websites</td>
</tr>
<tr>
<td>Full-Time Employment</td>
<td># of full-time workers in the housekeeping industry</td>
<td>Bureau of Labor Statistics</td>
</tr>
<tr>
<td>Middle-skilled worker</td>
<td># of supervisors/managers in the housekeeping industry</td>
<td></td>
</tr>
<tr>
<td>Low-skilled worker</td>
<td># of janitors/cleaners in the housekeeping industry</td>
<td></td>
</tr>
<tr>
<td>Self-Employment</td>
<td># of self-employed workers in the housekeeping industry</td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td># of unemployed workers in the housekeeping industry</td>
<td></td>
</tr>
<tr>
<td>CollegeAbove</td>
<td>% of bachelor degree or higher</td>
<td>U.S. Census Bureau</td>
</tr>
<tr>
<td>ServiceShare</td>
<td>% service employment in total employment</td>
<td></td>
</tr>
<tr>
<td>TechShare</td>
<td>% of high technology employment in total employment</td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>Total population (log-transformed)</td>
<td></td>
</tr>
<tr>
<td>SexRatio</td>
<td>The ratio of male to female in total population</td>
<td></td>
</tr>
<tr>
<td>OldRatio</td>
<td>The ratio of the olders above 65 to the total labor force</td>
<td></td>
</tr>
<tr>
<td>White Ratio</td>
<td>% of Caucasions in total population</td>
<td></td>
</tr>
<tr>
<td>Poverty Percentage</td>
<td>% of the total population below the poverty line</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>GDP per capita (log transformed)</td>
<td></td>
</tr>
</tbody>
</table>

Occupation Categories in the Housekeeping Industry

1011: First-line supervisors/managers of housekeeping and janitorial workers
1012: First-line supervisors/managers of landscaping, lawn service, and groundskeeping workers.
2011: Janitors and cleaners, except maids and housekeeping.
2012: Maids and housekeeping cleaners.

Results

The regression results are presented in Table 3. Columns 1 and 2 present the estimates without and with county-specific linear trends. We find that the introduction of the TaskRabbit is associated with a significant decrease in the number of full-time workers (-2.9%, p<0.05) in the housekeeping industry, suggesting that the entry of TaskRabbit may reduce the full-time employment in the housekeeping industry.

The primary assumption of the DID model is that there is no difference in the pre-treatment trends between treated and untreated counties (i.e., parallel trend assumption). A violation of this assumption could be caused by nonrandom selection into certain areas. Following Autor et al. (2003), we replicate our analysis using a relative time model. This model helps to check whether a pre-treatment trends exists. Figure 1 plots the coefficients of the pre- and post-treatment dummies relative to the baseline year. As seen, none of the pre-treatment dummies are significant, implying that there are no significant differences in pre-treatment trends across counties. Finally, we observe a significant downward trend after the TaskRabbit entry.

Table 3. DID Estimation of TaskRabbit Entry on the Local Housekeeping Employment

<table>
<thead>
<tr>
<th></th>
<th>DV: log(Full-Time Employment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>TaskRabbitEntry</td>
<td>-0.0289***</td>
</tr>
<tr>
<td>All Covariates</td>
<td>YES</td>
</tr>
<tr>
<td>County Fixed-Effects</td>
<td>YES</td>
</tr>
<tr>
<td>Year Fixed-Effects</td>
<td>YES</td>
</tr>
<tr>
<td>County-Specific Time Trends</td>
<td>NO</td>
</tr>
<tr>
<td># of Observations</td>
<td>8,040</td>
</tr>
<tr>
<td># of Counties</td>
<td>804</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.291</td>
</tr>
</tbody>
</table>

Notes: Covariates in Table 2 are all included but omitted here for brevity. Robust standard errors (clustered in counties) in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Robustness Checks

The first concern is that the introduction of TaskRabbit may endogenously be determined by the past employment status in the local housekeeping industry. To address this issue, we use discrete time hazard model to predict TaskRabbit entry using time-varying covariates, plus the employment level in one year, two years, and three years prior to the TaskRabbit entry. We do not find evidence of such a reverse causality.

Second, there may exist a selection issue, that is, counties that have yet been chosen by TaskRabbit might not be an ideal counterfactual to the treated counties. To remedy this, we use Coarsened Exact Matching to adjust the balance of time-varying covariates (i.e., population, unemployment rate, education level, poverty level) between treated and untreated counties and replicate the regression. The results remain consistent.

Third, we consider alternative operationalization of treatment radius. We currently estimate the effect at the county level, which may be larger than the service scope (i.e., a city) of TaskRabbit. To mitigate this concern, we replicate the model using MSA-level data, and we find that the effects remain constant.

Last, we consider the distribution of dependent variables and vary our empirical specifications. Our current dependent variable is measured by the count of full-time workers in the housekeeping industry. Skewed as the count variable, we have used logarithm transformation to rule out outliers and to interpret the OLS estimates as percentage changes. However, normality assumption of the OLS may not be satisfied here. Alternatively, we use negative binomial estimators. The observed effects still hold.

Underlying Mechanisms: Redistribution Effect

To further explore the effect of TaskRabbit on full-time workers with different skill levels, we classify two groups in the total housekeeping employment: (i) first-line supervisors and managers (Occupation codes as 1011 and 1012 in Table 2) and, (ii) janitors and cleaners (2011 and 2012 in Table 2). Per extant labor economics studies (e.g., Autor and Dorn, 2013), the first group belongs to middle-skilled workers, while the second group belongs to the low-skilled workers. Such categorization is based on the average income level of occupations1. We replicate the main analysis for employment of both subgroups.

Table 4 shows the results. Interestingly, we find that the TaskRabbit entry has heterogeneous impacts across distinct skill levels of workers. In particular, while TaskRabbit entry is associated with a significant decrease in employment of middle-skilled cognitive workers (supervisors and managers) (-0.055, p<0.05), the effects on the low-skilled workers (janitors and cleaners) are not significant.

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1 Income information is acquired through occupational employment statistics of Bureau of Labor Statistics.
There could be two plausible explanations for the decline of full-time employment. First, this gig platform may replace first-line supervisors and managers by directly matching and locating janitors and cleaners to local housekeeping demand via the platform. In other words, the gig platform may substitute managers who match demand and supply offline. Therefore, we expect to see that middle-skilled workers become unemployed or switch to other related occupations after the entry of TaskRabbit. We herein call such a labor redistribution the “Unemployment Hypothesis” for the skill-substitution role of online gig platforms. Specifically, if the Unemployment Hypothesis holds, we would expect that the effect would be weaker for low-skilled workers since they have limited skills to adopt the new form of technology.

Second, it is also possible that the rise of gig platforms attracts the managers to the platform from their traditional businesses in the same industry. Managers could exploit the high matching efficiency of this platform to recruit and supervise janitors and cleaners more efficiently. The platform also offers flexibility and autonomy to these middle-skilled workers. Hence, we may expect to see that managers move away from traditional businesses to start up new businesses by leveraging such gig platforms as TaskRabbit. We herein call such a labor redistribution the “Entrepreneurship Hypothesis” for the skill-complementary role of online gig platforms as they encourage local entrepreneurship as a form of self-employment.

To test which hypothesis (“Unemployment” or “Entrepreneurship”) dominates as underlying mechanism that drive the observed decline in full-time employment, we have collected data on unemployment and self-employment in the housekeeping industry, and the employment of related occupations. Unemployment data is derived from the US Census Bureau, while self-employment data from US Bureau of Labor Statistics. Self-employed workers are the workers who work for profit or fees in their own business, profession, trade, or farm (Bureau of Labor Statistics). There are two types of self-employed workers: (i) incorporate and (ii) unincorporate. The first category contains workers who have their own businesses, while the second contains workers who work temperately and flexibly or are called “freelancers”. We combined both these categories to construct the measure for the number of local self-employed workers in the housekeeping industry. We acquire the related occupations information based on the occupation definition in O*Net database. These groups of occupations require the similar kinds of skills and are easy for workers to transfer. We replicate the DID model to examine the impacts of TaskRabbit entry on the number of unemployed and self-employed workers in the housekeeping industry and number of workers in the related occupations.

Table 5 shows the results. Interestingly, we find that while the introduction of TaskRabbit does not significantly affect unemployment and related occupations (Column 1 and 3), it statistically significantly increases the number of self-employed workers in the housekeeping industry by 13.98% (p<0.01, Column 2). These findings support the “Entrepreneurship Hypothesis” instead of “Unemployment Hypothesis”. It has a significant implication that, instead of crowding out local employment (i.e., making workers unemployed or moving to other industries), gig platforms may complement workers, especially cognitive skilled (or middle-skilled) workers, by redistributing them towards more local entrepreneurship activities.

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2 We include four groups of housekeeping related occupations: 1) Protective Service, (2) Food Preparation and Serving, (3) Personal Care and Service, and (4) Transportation and Material Moving Service.
Instead, gig platforms facilitate labor redistribution. To directly interview the service providers from the TaskRabbit platform to obtain deeper insights on how TaskRabbit has changed the traditional housekeeping businesses. Finally, our empirical evidence is not based on an ideal randomized controlled experiment. We are undertaking more validation and falsifications to check the robustness of our findings. To conclude, this study demonstrates that the emergence of gig platforms significantly affects offline labor markets. While gig platforms reduce the number of cognitive workers who match labor demand and supply as gig platforms do, they do not reduce the number of workers. Instead, gig platforms facilitate labor redistribution, thus particularly boosting local entrepreneurship.

**Table 5. DID Estimation of TaskRabbit Entry on Unemployment and Self-employment in the Housekeeping Industry**

<table>
<thead>
<tr>
<th></th>
<th>DV: log(Unemployment)</th>
<th>DV: log(Self-employment)</th>
<th>DV: log(related Occupations)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>TaskRabbitEntry</td>
<td>-0.0095</td>
<td>0.136***</td>
<td>-0.0237</td>
</tr>
<tr>
<td></td>
<td>(0.0705)</td>
<td>(0.0389)</td>
<td>(0.0283)</td>
</tr>
<tr>
<td>All Covariates</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>County Fixed Effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>County-Specific Time Trends</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td># of Observations</td>
<td>4,130</td>
<td>4,130</td>
<td>4,130</td>
</tr>
<tr>
<td># of Counties</td>
<td>413</td>
<td>413</td>
<td>413</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.01</td>
<td>0.055</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Note: Only 413 counties here have consistently been identified in unemployment and self-employment data. Robust standard errors (clustered in counties) in parentheses ** p<0.01, * p<0.05, * p<0.1

**Discussion and Conclusion**

We study the impact of gig platforms on the local labor market. Exploiting the geographical and temporal expansion pattern of TaskRabbit into US counties in 2006-2015, we observe a significant decrease in full-time employment in the local housekeeping industry in the TaskRabbit-served areas. We also find that the middle-skilled cognitive workers (i.e., managers and supervisors) in the housekeeping industry decrease significantly after the TaskRabbit entry, which has no significant impacts on low-skilled (manual) workers (i.e., cleaners and janitors). This suggests that gig platform do not “crowd out” low-skilled workers in the industry. To further explore the decrease in middle-skilled employment (i.e., managers and supervisors), we find that the corresponding self-employment in the industry significantly increases, while the unemployment holds constant. The findings, while need further corroboration, imply that gig platforms like TaskRabbit do not crowd out middle-skilled workers but facilitate their mobility towards local entrepreneurship activities in order to reap the benefits of high matching efficiency on the gig platforms.

This study makes two key theoretical and empirical contributions. First, this study leverage and extends SBTC ("Skill-Biased Technical Change") theory to analyze the impact of a new technology, the gig platform, on offline local labor markets (Autor et al. 2003, Bekman et al. 1998). Second and relatedly, our study contributes to the emerging literature on the broader impact of the gig economy on online labor markets. Extant studies have provided competing predictions and evidence on the role of gig economy platforms (Fraiberger and Sundararajan 2017, Schor 2017). We offer comprehensive and robust empirical evidence on whether, how, and why gig platforms affect local labor markets and redistribute employment by skills.

This study provides insightful practical and policy implications. The workers in traditional industries can better understand the nature of gig-economy platforms and how they may influence their future careers. The policymakers and social planners should be aware of the significant role of platforms on local labor mobility and regional economy. Developers of such platforms could use our findings on the heterogeneous effects across skills to better optimize their services to incubate local entrepreneurship.

Given the nature of this research-in-progress, this current research has limitations, which directs to several follow-up studies for the next steps. First, while we have proposed hypotheses and offered suggestive evidence on the labor mobility in response to the availability of gig platforms, we would ideally need richer data and more rigorous analyses to parse the underlying mechanisms. We are currently collecting data of part-time, self-employed, and unemployed employment across different skill levels. Second, we would like to directly interview the service providers from the TaskRabbit platform to obtain deeper insights on how TaskRabbit has changed the traditional housekeeping businesses. Finally, our empirical evidence is not based on an ideal randomized controlled experiment. We are undertaking more validation and falsifications tests to check the robustness of our findings. To conclude, this study demonstrates that the emergence of gig platforms significantly affects offline labor markets. While gig platforms reduce the number of cognitive workers who match labor demand and supply as gig platforms do, they do not reduce the number of workers. Instead, gig platforms facilitate labor redistribution, thus particularly boosting local entrepreneurship.
References


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