informs
https://pubsonline.informs.org/journal/isre

INFORMATION SYSTEMS RESEARCH
Vol. 36, No. 3, September 2025, pp. 1354–1374
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Skill-Biased Technical Change, Again? Online Gig Platforms and Local Employment

Xue Guo,[a] Zhi (Aaron) Cheng,[b] Paul A. Pavlou[c,*]

[a] Robinson College of Business, Georgia State University, Atlanta, Georgia 30303; [b] Department of Management, London School of Economics and Political Science, London WC2A 2AE, United Kingdom; [c] Miami Herbert Business School, University of Miami, Miami, Florida 33146

*Corresponding author

Contact: xguo18@gsu.edu, https://orcid.org/0000-0002-0580-9488 (XG); a.z.cheng@lse.ac.uk, https://orcid.org/0000-0002-2070-3761 (Z(A)C); pavlou@miami.edu, https://orcid.org/0000-0002-8830-5727 (PAP)

Received: May 20, 2022
Revised: August 18, 2023; May 23, 2024
Accepted: August 7, 2024
Published Online in Articles in Advance: November 13, 2024

https://doi.org/10.1287/isre.2022.0307

Abstract. Online gig platforms have the potential to influence employment in existing industries. Popular press and academic research offer two competing predictions: First, online gig platforms may reduce the supply of incumbent workers by intensifying competition and obsoleting certain skills of workers; or, second, they may boost the supply of workers by increasing client-worker matching efficiency and creating new employment opportunities for workers. Yet, there has been limited understanding of the labor movements amid the rise of online gig platforms. Extending the skill-biased technical change literature, we study the impact of TaskRabbit—a *location-based* gig platform that matches freelance workers to local demand for domestic tasks (e.g., cleaning services)—on the local supply of incumbent, work-for-wages housekeeping workers. We also examine the heterogeneous effects across workers at different skill levels. Exploiting the staggered TaskRabbit expansion into U.S. cities, we identify a significant decrease in the number of incumbent housekeeping workers after TaskRabbit entry. Notably, this is mainly driven by a disproportionate decline in the number of middle-skilled workers (i.e., first-line managers, supervisors) whose tasks could easily be automated by TaskRabbit's matching algorithms, but not low-skilled workers (i.e., janitors, cleaners) who typically perform manual tasks. Interestingly, TaskRabbit entry does *not* necessarily crowd out middle-skilled housekeeping workers, neither laying them off nor forcing them to other related occupations; rather, TaskRabbit entry supports self-employment within the housekeeping industry. These findings imply that online gig platforms may not naively be viewed as skill biased, especially for low-skilled workers; instead, they *redistribute* middle-skilled managerial workers whose cognitive tasks are automated by the sorting and matching algorithms to explore new self-employment opportunities for workers, stressing the need to reconsider online gig platforms as a means to reshape existing industries and stimulate entrepreneurial endeavors.

History: Manju K. Ahuja, Senior Editor; Jason Chan, Associate Editor.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/isre.2022.0307.

Keywords: online gig platforms • employment • skill-biased technical change • difference-in-differences • generalized synthetic control

1. Introduction

Online gig platforms have, in the recent decade, facilitated the shift of service employment from permanent employment to on-demand gig work (Sundararajan 2017). For example, TaskRabbit is a popular *location-based* online gig platform that enables matching between workers and clients for service activities (e.g., cleaning), which naturally take place offline. The rise of these gig platforms has brought challenges to traditional incumbent industries[1] due to their superior matching algorithms (Cramer and Krueger 2016), flexible work schedules (Hall and Krueger 2018), and lower entry barriers (Schwellnus et al. 2019). Hence, a critical question arises: Does the rise of gig platforms destroy traditional industries? The popular press and academic research offer competing predictions. First, online gig platforms may intensify competition among traditional businesses and workers by offering more cost-effective services, thus reducing the need for existing workers (Cramer and Krueger 2016, Schor 2017). Second, in contrast, online gig platforms may create new job opportunities by reducing search costs for workers and clients, thus leading to net employment growth (Fraiberger and Sundararajan 2017). Although both predictions have been reflected in recent anecdotes,[2] there has been a lack of theoretical understanding and rigorous empirical analysis on the effects of online gig platforms on local employment. Hence, our first objective is to examine how online gig platforms may affect the supply of incumbent workers[3] in service occupations.

Our study also explores the heterogenous effects of online gig planforms on workers at different skill levels (i.e., low-skilled versus middle-skilled). The ever-lasting discourse on the interplay between technology, skills, and labor suggests that technology has varied effects on workers with different skill sets (Violante 2008). Notably, skill-biased technical change (SBTC) theory suggests that technology raises the relative demand for high-skilled workers by boosting their productivity while substituting low-skilled workers (Card and DiNardo 2002, Acemoglu and Autor 2011). As a technological innovation at its core, online gig platforms may exert disproportionate effects on workers at different skill levels. In this study, we examine the role of online gig platform entry on local employment in service occupations in general, with an empirical focus on the housekeeping occupations.[4] Service occupations, such as housekeeping have experienced disruption from the entry of online gig platforms, and they have been a major focus in the recent literature on technology and labor (Gatta et al. 2009, Acemoglu and Autor 2011). We focus on two types of workers[5]—low-skilled and middle-skilled in housekeeping occupations (Table 1)—who may be differentially affected by TaskRabbit entry. Low-skilled workers, such as janitors and cleaners, are service workers that perform intensive manual tasks; whereas middle-skilled workers, such as first-line supervisors and managers, perform routine cognitive (e.g., matching and supervising) tasks, which might overlap with the functions (e.g., matching service demand and supply) mediated by online gig platforms, such as TaskRabbit. We categorize incumbent housekeeping workers into middle-skilled and low-skilled workers based on their skill percentiles[6] rank in all occupations, following the seminal classification by Autor and Dorn (2013). In a typical service context, online gig platforms could play a crucial role in matching and supervising tasks, resembling the job functions of middle-skilled workers, with arguably a lesser impact on low-skilled workers (details in Section 3.3.2). Thus, our second objective is to examine the differential effects of online gig platforms on workers at different (low versus medium) skill levels.

Motivated by the above theoretical and empirical accounts, we ask the following research questions. (i) *How and why does the entry of an online gig platform (i.e., TaskRabbit) affect the number and wages of incumbent workers in service occupations (i.e., housekeeping services)?* (ii) *Does this impact vary across workers at different skill levels (middle-skilled versus low-skilled workers), and if so, how?*

To empirically answer these research questions, we study TaskRabbit, one of the earliest and largest online gig platforms that match freelancers with local domestic housekeeping tasks, such as cleaning and gardening. Since its inception in 2008, TaskRabbit had gradually expanded and operated in more than 40 cities by 2018. We collected the expansion history of TaskRabbit in the United States from 2008 to 2018 and consolidated a unique longitudinal data set of local employment in housekeeping occupations across the United States. This data set aggregates data from the Census Bureau, Occupational Information Network (O*NET) database, and American Community Survey, covering occupational information at the MSA (metropolitan statistical area) level for consecutive years between 2005 and 2018. We exploited the quasi-experimental setting where TaskRabbit expanded across U.S. cities at different times, employing the difference-in-differences (DiD) approach with location and time fixed effects to estimate its effect on the employment of incumbent workers.

Econometrics analyses yield notable findings. We observe a disproportionate decrease (-7.1%, $p < 0.001$) in the number of incumbent housekeeping workers in locations where TaskRabbit has operated compared with locations where TaskRabbit did not enter. We do not find statistically significant effects on average annual wages. Interestingly, the employment effects vary across housekeeping workers at different skill levels. Specifically, there is a statistically significant decrease in the number of incumbent middle-skilled workers (e.g., first-line managers, supervisors) after TaskRabbit entry, while the number of incumbent low-skilled workers (e.g., janitors, cleaners) remains steady (statistically insignificant) over the same period. Notably, these effects remain robust and consistent under different model specifications and samples of

Table 1. Housekeeping Workers with Different Skills

Skill level	Tasks examples	Occupation examples
Middle-skilled	• Plan and prepare employee work schedules • Supervise in-house services • Inspect work performed to ensure that it meets specifications and established standards	First-line supervisors and managers of housekeeping and janitorial workers
Low-skilled	• Service, clean, or supply restrooms • Clean building floors by sweeping, mopping, or vacuuming • Gather and empty trash	Janitors and cleaners, maids and housekeeping cleaners

Note. Definitions and examples are adapted from the O*NET Occupational Database.

MSAs and periods. Furthermore, we employ a newly developed heterogeneity-robust DiD model specification to address the limitations of our baseline estimation with multiple entry periods (Callaway and Sant'Anna 2021). Additionally, we use the generalized synthetic control (GSC) method, which constructs a counterfactual for TaskRabbit-operated locations, to better satisfy the parallel trend assumption of the pretreatment employment (Xu 2017). Both estimates corroborate our baseline results. Taken together, our analyses consistently indicate that middle-skilled incumbent housekeeping workers, relative to low-skilled workers, are more significantly affected by the entry of online gig platforms, such as TaskRabbit.

How can we explain the decline in incumbent middle-skilled workers? Drawing on the literature on online gig platforms and labor economics (Berger et al. 2018, Li et al. 2021), we hypothesize three plausible labor movements: (i) the *unemployment effect*, that is, online gig platforms replace incumbent (middle-skilled) workers, raising unemployment; (ii) the *relocation effect*, that is, online gig platforms relocate incumbent middle-skilled workers to similar occupations; and (iii) the *self-employment effect*, that is, online gig platforms redistribute incumbent middle-skilled workers to self-employment. Using data on individual-level employment status and MSA-level business establishments, we observe a statistically significant movement of incumbent middle-skilled workers toward self-employment in the housekeeping industry, following TaskRabbit entry. Interestingly, the rise in self-employment primarily falls under the *incorporated* self-employment category, representing entrepreneurs who start their own businesses, as opposed to the *unincorporated* self-employment category, representing freelancers and independent contractors. Besides, there is a significant decrease in incumbent middle-skilled housekeeping workers becoming unemployed, and no significant effect on employment in other skill-related occupations over the same period. These results corroborate the *self-employment effect*, but not the other two labor movements. Integrating the main employment effects of online gig platforms with the observed labor movement, our study shows that online gig platforms may *not* naively be viewed as skill-biased; instead, their market entry exerts a *labor redistribution effect* that shifts incumbent middle-skilled workers to self-employment.[7]

Implications stem from this work. First, our study contributes to the literature on online gig platforms and their labor market outcomes (Cramer and Krueger 2016, Burtch et al. 2018). In response to the debate on the pros and cons of online gig platforms on incumbent local employment (Sundararajan 2017, pp. 159–196), our study is, to our knowledge, the first to offer a rigorous analysis of how online gig platforms affect the supply of incumbent workforce in service occupations like housekeeping. We provide theoretical underpinnings and rigorous empirical evidence that online gig platforms may *redistribute* middle-skilled housekeeping workers from work-for-wages employment to self-employment.

Second, our findings contribute to SBTC theory (Acemoglu and Autor 2011, Autor and Dorn 2013) by exploring the differential effects of online gig platforms on workers at different skill levels. Specifically, we make two important extensions to the theory: (i) we study a new form of technology—online gig platforms—and its labor implications, whereas existing information systems (IS) and economics literature has mainly focused on automation in the labor market (Card and DiNardo 2002, Dixon et al. 2021), and (ii) the labor movement of middle-skilled housekeeping workers highlights a unique and under-studied role of online gig platforms, which is not simply explained as skill biased, but rather having a labor redistribution effect that shifts workers whose tasks can easily be replaced by the functions of the online gig platforms from work-for-wages employment to self-employment and other entrepreneurial ventures.

Finally, this study offers practical insights. For policymakers, our findings add to the debate on the labor implications of online gig platforms (Cramer and Krueger 2016, Schor 2017, Zervas et al. 2017). Although online gig platforms may decrease the number of incumbent workers, they can stimulate local labor markets by redistributing these wage workers to self-employment, a novel avenue for encouraging new entrepreneurial endeavors. For incumbent workers in service occupations, it is crucial to understand the labor implications of online gig platforms and take the initiative to adapt their advertised job tasks and offerings to accommodate workers' needs (e.g., flexibility and autonomy). Beyond the simplified view of labor substitution through automation that prior research has focused on, our study sheds light on the nuanced role of online gig platforms in redistributing incumbent workers to self-employment, fostering a rise in entrepreneurial opportunities for housekeeping workers to start their own small businesses.

2. Background

2.1. Housekeeping Occupations

We use housekeeping occupations as our empirical context for several reasons: First, housekeeping represents a service occupation increasingly affected by technological advances, garnering significant attention in recent technology and labor studies (Frey and Osborne 2017). Prior research has explored technology's role in complementing low-skilled workers performing manual tasks (e.g., truck driving), whereas substituting middle-skilled workers engaged in routine and readily automated cognitive tasks (e.g., record keeping) (Autor and Dorn 2013). As an emerging technological innovation, online gig platforms may influence the workforce beyond mere automation by creating new job opportunities for incumbent workers. Yet, the role of online gig platforms on housekeeping occupations remains underexplored.

Second, housekeeping occupations involve manual tasks (e.g., cleaning) that closely align with the offerings of online gig platforms that specialize in domestic tasks (e.g., TaskRabbit). Traditionally, the demand for housekeeping services and the corresponding labor supply were matched offline, typically through phone calls or direct visits to service providers. Online gig platforms, however, facilitate automated matching via their algorithms, potentially disrupting the traditional employment landscape for incumbent housekeeping businesses and existing workers.

Finally, the distinct skill levels among workers in housekeeping occupations—comprising low-skilled workers (i.e., cleaners, janitors) and middle-skilled workers (i.e., first-line managers, supervisors)—suggest the potential for disproportionate effects from online gig platforms. This skill-based division allows for an ideal framework to investigate whether gig platforms induce a skill-biased technical change. Table 2 presents the occupations of middle- and low-skilled workers within housekeeping businesses.

2.2. Focal Online Gig Platform: TaskRabbit

We examine the impact of online gig platforms on incumbent housekeeping workers by focusing on TaskRabbit, one of the largest gig platforms offering domestic services. Although several platforms offer housekeeping services (see Section 4.5.4 for a detailed discussion), we select TaskRabbit for three primary reasons: First, the entry of TaskRabbit exhibits geographical and temporal variations. The platform has progressively expanded its services to more than 40 U.S. cities from 2008 to 2018 (See details in Tables A1 and A2 in Online Appendix A). The staggered expansion allows us to estimate changes in local employment before and after the platform entry compared with the changes in locations where the platform did not enter over the same period. Second, TaskRabbit, founded in 2008, stands as one of the earliest and largest gig platforms enabling clients to outsource small offline domestic tasks (e.g., cleaning) to local independent workers (Isaac 2015). TaskRabbit serves a representative and substantial gig platform that has potentially disrupted the traditional housekeeping industry. Finally, although the platform matches housekeeping demand and labor supply online, it restricts workers to performing services *offline* and *locally* within delimited geographic areas (e.g., MSAs). This feature dismisses the concern regarding potential interference due to labor movement across geographical locations, enabling a comparison of local employment changes after TaskRabbit entry between TaskRabbit-treated locations versus untreated (no TaskRabbit entry) locations.

3. Literature Review and Theoretical Hypotheses

3.1. Role of Online Gig Platforms in Labor Markets

The distinctive features of online gig platforms empower their impact on local labor markets. First, online gig platforms exhibit enhanced efficiency compared with traditional housekeeping businesses in facilitating key functions, such as matching and supervision processes (Cramer and Krueger 2016, Einav et al. 2016). Specifically, these platforms excel in connecting workers with clients based on service requirements and preferences, thus reducing search costs and enhancing matching efficiency (Schwellnus et al. 2019). Through online gig platforms, clients typically find workers through three steps: (i) selecting the task, (ii) choosing workers from a recommendation list, and (iii) paying for services after workers perform the desired task. In contrast, traditional businesses connect to their clients through different online or offline processes (e.g., emails, mail, direct phone calls), thus incurring higher matching costs. For example, research shows that Uber exhibits significantly shorter wait times (Rayle et al. 2016) and higher capacity utilization (fraction of time or mileage a driver has a client) than traditional taxis (Cramer and Krueger 2016). Moreover, in the supervision process, establishing trust and reputation can be challenging through traditional means. Online gig platforms

Table 2. Housekeeping Occupations

Skill level	Standard occupational classification (SOC) code
Middle-skilled	37-1011 First-line supervisors/managers of housekeeping and janitorial workers
	37-1012 First-line supervisors/managers of landscaping, lawn service, and groundskeeping workers.
Low-skilled	37-2011 Janitors and cleaners, except maids and housekeeping.
	37-2012 Maids and housekeeping cleaners.
	37-2021 Pest control workers
	37-3011 Landscaping and Groundskeeping Workers

Notes. Following the classification method used by Autor and Dorn (2013), we classify the six housekeeping occupations into the middle-skilled and low-skilled based on their skill percentiles rank in all occupations. Routine-intensive occupations (e.g., 37-1011) fall in the middle part of the distribution, and manual occupations (e.g., 37-2011) fall in the bottom part of the distribution.

address this challenge with user review systems, which are simple to implement and carry substantial impact (Sundararajan 2017), regulating workers' behavior and incentivizing improved performance to attract consumers (Einav et al. 2016).

Second, online gig platforms offer greater flexibility and autonomy, allowing freelance workers to tailor their work schedules (Li et al. 2021). While traditional businesses typically dictate workers' schedules and wages, online gig platforms empower workers with more control over how they want to actually work (Jenkins et al. 2023). Hall and Krueger (2018) suggest that flexibility is the primary reason that workers are attracted to online gig platforms. Berger et al. (2019) further highlight its positive association with gig workers' subjective well-being. Therefore, online gig platforms may attract workers who are seeking higher flexibility and autonomy from their jobs.

Third, online gig platforms lower barriers for workers to enter the job market, thus promoting self-employment opportunities (Vallas and Schor 2020). Traditional self-employment usually requires paying the costs of starting a business and reaching a critical mass of clients.[8] The advent of online gig platforms reduces such entry barriers, providing effective mechanisms (e.g., online rating) to signal worker quality (Benson et al. 2020) and an existing client base to leverage (Schwellnus et al. 2019), thereby largely diminishing the cost of self-employment.

A nascent line of research has begun exploring the role of online gig platforms in various labor market outcomes (see Table F1 in Online Appendix F for a list of selected studies). For example, Li et al. (2021) show that online gig platforms offer flexible work opportunities for low-skilled and unemployed workers, thereby reducing overall unemployment. Connecting the proliferation of online gig platforms to job opportunities, Burtch et al. (2018) identify a negative relationship between Uber entry and local entrepreneurial activity, implying that online gig platforms offer viable work opportunities for the unemployed or underemployed.

Nevertheless, this research strand has yet to provide adequate theoretical understanding and empirical evidence on the interplay between online gig platform expansion and *incumbent* work supply. It is not straightforward to predict this relationship because the net total impact depends on two distinct effects—substitution and complementarity. Although new gig platforms may heighten the operational efficiency of service businesses, potentially reducing the demand for incumbent workers (Cramer and Krueger 2016), they may also create new job opportunities by reducing search costs (Schwellnus et al. 2019). This study aims to reconcile this tension by theorizing and presenting robust empirical evidence on the impact of online gig platforms on the incumbent workforce. Furthermore, considering the skill structures of incumbent workers, we theoretically and empirically investigate the type of workers most likely to be affected, and the manner in which they may be impacted, by online gig platforms.

3.2. Technology and Employment

This work also builds on existing research on the interplay between technology and employment. The labor economics literature has long debated the interdependence among technological advances, skill requirements, and employment dynamics (Card and DiNardo 2002, Acemoglu and Restrepo 2019). A canonical theory in this discourse is SBTC (Acemoglu 2002, Autor et al. 2003), which posits that technological progress *complements* skilled workers by boosting their relative productivity and *substitutes* unskilled workers by automating their tasks. For example, the widespread adoption of workplace computers and technologies has led to the automation of routine-intensity jobs (e.g., cashiers, calculators), resulting in the substitution of low-skilled workers. The ubiquity and affordability of computers have also spurred the demand for high-skilled workers capable of effectively leveraging these tools, a phenomenon known as capital-skill complementarity (Krusell et al. 2000, Acemoglu 2002). Accordingly, the literature documents a shift in labor supply, favoring nonroutine tasks, especially in computer-intensive industries (Violante 2008). Autor and Dorn (2013) elucidate the *polarized* distribution of employment among skilled occupations; they show that the growth of high-skilled and low-skilled jobs often occurs at the expense of middle-skilled workers whose tasks are codifiable, easily automated, and thus susceptible to technological displacement. In contrast, low-skilled workers (e.g., janitors, cleaners), whose roles entail intensive manual tasks and interpersonal interactions, are less vulnerable to automation. Recent SBTC research has expanded to investigate emerging technological innovations (e.g., artificial intelligence (AI), robots), revealing their potential to affect occupations involving both manual and cognitive tasks. For example, Agrawal et al. (2019) suggest that AI may substitute occupations involving prediction tasks (e.g., forecasting) while complementing occupations requiring decision-related tasks (e.g., strategic planning). Dixon et al. (2021) demonstrate that, although robots can replace managerial roles involving supervision and monitoring, they can simultaneously create new work opportunities for both high- and low-skilled workers, supporting the polarized version of SBTC theory.

Our study extends the SBTC literature by examining the impact of a rising, but rather underexplored, technological innovation, *online gig platforms*, on the employment of incumbent workers with different skill sets. While the SBTC literature has mainly focused on the impacts of general-purpose technologies (GPTs) across diverse sectors, online gig platforms represent a specialized technology that may disrupt service occupations.

Our study aims to contextualize their employment implications by emphasizing the unique features of gig platforms, including matching and supervising, work flexibility, and lower entry barriers, beyond the general features (e.g., automation) of a GPT. In terms of labor market outcomes, GPTs typically create new occupations (e.g., computer-related) or relocate the workforce to other occupations (e.g., workers in routine roles shifting to more analytic occupations) (Brynjolfsson et al. 2018). In contrast, online gig platforms provide opportunities for "gig work" (outside traditional companies), thus promoting a shift toward self-employment in the labor market. Against this backdrop, we argue that online gig platforms may not simply exhibit bias against certain (low-skilled) occupations, but they may redistribute workers across employment modes. Yet, prior research has yet to contextualize this potential of online gig platforms on incumbent employment, underscoring the novelty of our theoretical and empirical investigations.

3.3. Hypotheses Development

In this section, we theorize how the introduction of online gig platforms influences the employment of incumbent workers. We develop hypotheses concerning (i) the overall employment impact of online gig platforms on incumbent workers, (ii) the differential effects across workers at different skill levels, and (iii) the potential mechanisms through which gig platforms redistribute labor to explain (i) and (ii).

3.3.1. Overall Employment Effect on Incumbent Housekeeping Workers. We begin our theorization by developing hypotheses for the overall effect of online gig platform entry on the supply of incumbent workers. Specifically, we elucidate two countervailing theoretical predictions:

On the one hand, the introduction of online gig platforms might adversely affect incumbent workers by augmenting the operational efficiency of housekeeping companies. Specifically, online gig platforms streamline business operations by automating job matching, scheduling, and supervision processes (Cramer and Krueger 2016, Horton 2017). This enhanced operational efficiency significantly reduces the need for manual coordination and oversight, tasks that traditionally consume considerable administrative resources. For instance, housekeeping businesses leveraging gig platforms can effectively manage job assignments and customer interactions through automatic matching algorithms and review systems (Möhlmann et al. 2021). Furthermore, online gig platforms enhance worker visibility by promoting profiles to a broader audience, thereby reducing marketing expenses (Einav et al. 2016). Consequently, increased efficiencies may reduce the demand for incumbent workers in housekeeping companies.

Online gig platforms may attract incumbent workers, potentially negatively impacting their incumbent employment. A key advantage of online gig platforms lies in their provision of work flexibility and autonomy (Vallas and Schor 2020, Anderson et al. 2021). Unlike incumbent roles with fixed schedules and rigid hierarchies, online gig platforms offer significant flexibility, enabling workers to choose when and where they work—an attribute particularly appealing to workers seeking superior work-life balance (Hall and Krueger 2018). Online gig platforms offer autonomy over tasks and work styles, allowing workers to innovate and tailor their approach to better align with their skills and preferences, thus enhancing their job satisfaction. As a result, incumbent workers who appreciate these benefits may opt to leave their current positions, potentially shifting customer demand to platforms and reducing demand for incumbent workers. Summarizing the theoretical arguments above, the entry of online gig platforms might result in a smaller workforce and lower wages for incumbent workers. Hence, we propose Hypothesis 1a for testing:

Hypothesis 1a. *TaskRabbit entry is negatively associated with* (i) *the number and* (ii) *wages of incumbent workers in housekeeping occupations.*

On the other hand, the entry of online gig platforms may positively affect incumbent workers by creating more employment opportunities. First, gig platforms reduce search costs for housekeeping services (Goldfarb and Tucker 2019), potentially boosting the demand for incumbent workers (Schwellnus et al. 2019). For instance, the advanced sorting and filtering capabilities of online gig platforms enable effective matching between clients and workers (Gong 2016), minimizing labor market inefficiencies often referred to as "slack." Nandakumar (2020) notes that following the introduction of ride-sharing services in New York, the demand for taxi drivers increased as it became easier for clients to find a taxi. Second, online gig platforms offer an important supplemental source of income. Prior studies have demonstrated that online gig platforms can serve as a stable income source for workers due to their lower entry barriers and flexible work schedules (Schor et al. 2020). Summarizing the above theoretical possibilities, we may observe a surge in employment for incumbent housekeeping workers following TaskRabbit entry. Hence, we propose a competing hypothesis (Hypothesis 1b) for empirical testing.

Hypothesis 1b. *TaskRabbit entry is positively associated with* (i) *the number and* (ii) *wages of incumbent workers in housekeeping occupations.*

While both hypotheses (Hypothesis 1a and Hypothesis 1b) are plausible, the net effect of online gig platform (TaskRabbit) entry on the employment of incumbent workers will depend on which hypothesis empirically dominates. This necessitates empirical analysis to determine the direction and magnitude of the overall net effect.

3.3.2. Employment Effect Heterogeneity Across Occupations. Next, we develop the theoretical underpinnings for the differential effects of online gig platforms on workers at different skill levels (low or middle) in the context of traditional housekeeping businesses.

Should online gig platforms detrimentally affect the employment of incumbent workers (i.e., if Hypothesis 1a holds), the adverse effect would be more pronounced for middle-skilled workers than for low-skilled ones. Online gig platforms might enhance operational efficiency by rendering incumbent middle-skilled workers obsolete when their tasks are replaceable by technology (Autor et al. 2003), such as scheduling and supervising services. Frey and Osborne (2017) show that 94% of middle-skilled housekeeping occupations can be computerized. Online gig platforms can automatically match clients and housekeeping workers, streamline transactions, and manage reviews (Vallas and Schor 2020), tasks that heavily overlap with the duties of incumbent middle-skilled workers. As a result, the demand for middle-skilled workers would decline if online gig platforms could more effectively manage low-skilled workers (Violante 2008). In contrast, online gig platforms cannot readily substitute low-skilled workers for in-person manual housekeeping tasks. Hence, online gig platforms may exhibit a greater bias *against*, and even substitute, incumbent middle-skilled workers compared with low-skilled workers. Accordingly, we hypothesize the following.

Hypothesis 2a. *The proposed negative effects of TaskRabbit entry on* (i) *the number and* (ii) *wages of incumbent housekeeping workers* (*Hypothesis* 1a) *are stronger for middle-skilled than for low-skilled workers.*

In contrast, if gig platforms positively boost the employment of incumbent workers (i.e., if Hypothesis 1b holds), we argue that the positive effect would be more pronounced for low-skilled workers than middle-skilled workers for several reasons. First, the entry of online gig platforms can directly elevate the demand for low-skilled workers, as they can readily perform such tasks. For instance, Dixon et al. (2021) suggest the adoption of robots leads to an increased demand for low-skilled workers capable of performing residual tasks that robots have not yet automated. In our setting, because TaskRabbit cannot replace the hands-on cleaning tasks performed by low-skilled workers, their demand is likely to rise. Second, the increase in middle-skilled worker employment might be slower due to their job functions overlapping with those of online gig platforms. With a substantial surge in low-skilled workers, a gradually growing demand for middle-skilled workers may follow to oversee and facilitate the matching of low-skilled workers. Yet, online gig platforms could counteract this surge by replacing a large portion of middle-skilled workers' jobs. Consequently, although rising industry demand can augment the overall supply of housekeeping workers, middle-skilled workers are arguably less affected than low-skilled workers. Therefore, we hypothesize the following.

Hypothesis 2b. *The proposed positive effects of TaskRabbit entry on* (i) *the number and* (ii) *wages of incumbent housekeeping workers* (*Hypothesis* 1b) *are stronger for low-skilled than for middle-skilled workers.*

3.3.3. Labor Redistribution Effect of Online Gig Platforms. We further explore the potential labor movements of incumbent workers after online gig platform entry. Should the negative effects of gig platforms on incumbent workers (Hypothesis 1a) outweigh the positive effect (Hypothesis 1b), we would expect a decrease in the supply of incumbent workers. If so, where are these incumbent workers going? We explore how the entry of online gig platforms redistributes workers to different employment modes, raising three mutually exclusive predictions: (i) the *unemployment effect*, that is, incumbent workers lose their jobs and thus become unemployment, (ii) the *relocation effect,* that is, incumbent workers move to skill-related other occupations, and (iii) the *self-employment effect*, that is, incumbent workers become self-employed in a similar (housekeeping) occupation.

3.3.3.1. Unemployment Effect. Online gig platforms, such as TaskRabbit, streamline the process of matching labor supply with local service demand, potentially displacing middle-skilled managers or supervisors in traditional housekeeping companies that share major functional overlaps with these online gig platforms. Studies indicate that automation can render such jobs obsolete (Ford 2015, Casey 2018) as technology often performs these functions more cost-effectively. After the entry of TaskRabbit, incumbent middle-skilled workers could face unemployment if deemed redundant, whereas low-skilled workers, whose roles do not overlap with the gig platform functionalities, might see stable or increased demand for their services. Thus, it is possible that TaskRabbit's entry might shift middle-skilled workers, rather than low-skilled ones, to unemployment. Thus, we propose the unemployment effect hypothesis (Hypothesis 3a).

Hypothesis 3a. *TaskRabbit entry is positively associated with a transition of middle-skilled housekeeping workers from work-for-wages employment to unemployment.*

3.3.3.2. Relocation Effect. Another option for incumbent workers is to move to related occupations in other sectors that require similar skill levels (Moscarini and Vella 2008). Prior research suggests that workers are more likely to shift to related occupations that share similar job skills, minimizing the need for extensive retraining (Robinson 2018, Cheng and Park 2020). In our context, with the emergence of platforms like TaskRabbit, middle-skilled housekeeping workers may leave their current roles and enter other skill-related (but nonhousekeeping) occupations, such as those that require similar levels of management and communication skills (Tables C1 and C2 in Online Appendix C). However, the situation differs for low-skilled workers, whose tasks are less substitutable by online gig platforms, which thus offers a scant incentive for them to relocate occupations. Accordingly, we propose the *relocation effect* hypothesis (Hypothesis 3b).

Hypothesis 3b. *TaskRabbit entry is positively associated with a movement of middle-skilled housekeeping workers from work-for-wages employment to employment in other skill-related service occupations.*

3.3.3.3. Self-Employment Effect. The third option we propose for incumbent workers is transitioning to self-employment, whether as independent contractors or business owners. First, online gig platforms notably lower barriers to self-employment entry (Vallas and Schor 2020, Silva and Moreira 2022), often requiring minimal prior experience, references, or qualifications for workers to become independent contractors on online gig platforms.[9] Meanwhile, for prospective business owners, although starting a new business carries inherent risks, online gig platforms help mitigate these risks by significantly reducing operational and marketing challenges through efficient matching algorithms and by providing access to an established client base (Einav et al. 2016). Besides, online gig platforms offer a form of financial security, allowing workers to sustain income as independent freelancers if their entrepreneurial ventures falter, thus reducing financial risk. For instance, Barrios et al. (2020) illustrate how ride-sharing platforms have spurred increased business registrations and improved loan accessibility by providing a stable income source for self-employed drivers.

For middle-skilled workers, the introduction of TaskRabbit offers viable pathways from wage-based employment to self-employment. First, as gig platforms enhance operational efficiencies for companies, the demand for middle-skilled workers in traditional roles may wane, potentially displacing them from incumbent employment. Consequently, these workers may opt for freelancer work to secure a reliable income. In addition, online gig platforms also make starting businesses a feasible option for middle-skilled workers possessing supervisory, managerial, and technological skills (see Online Appendices B and E for details), positioning them to use these capabilities for entrepreneurial opportunities (Fossen and Sorgner 2021).

In contrast, low-skilled workers may perceive limited incentives to transition from work-for-wages employment to becoming self-employed, whether as independent contractors or business owners. Despite the flexibility offered by online gig platforms, surveys indicate that low-skilled workers are reluctant to leave their occupations due to concerns over losing employment benefits, such as health insurance.[10] Hence, many low-skilled workers prefer occasional gig work to supplement income.[11] The nature of tasks typically performed by low-skilled workers, primarily labor-intensive manual tasks, coupled with insufficient managerial and technological skills (see Online Appendix B) and entrepreneurial experience (Lazear 2004), significantly reduce their likelihood of starting their own companies. These factors may collectively reinforce their preference for maintaining their existing wage-based employment status. These arguments suggest another plausible movement of incumbent middle-skilled, rather than low-skilled, workers toward self-employment following gig platform entry, leading to the *self-employment effect* hypothesis (Hypothesis 3c).

Hypothesis 3c . *TaskRabbit is positively associated with a movement of middle-skilled housekeeping workers from their work-for-wages employment to self-employment in housekeeping occupations.*

4. Data and Methods

4.1. Data

To empirically test our hypotheses, we consolidated a unique longitudinal data set from three major sources covering a period of 14 years from 2005 to 2018. First, we collected local employment data[12] (i.e., number and average annual wage of workers) using the Integrated Public Use Microdata Series (IPUMS) from the U.S. Census Bureau (Ruggles et al. 2019). This microlevel data set covers 1% of the U.S. population each year and includes anonymous individual-level information on employment status, occupation, wage, and location. This data set has widely been used in labor economics (Kerr and Lincoln 2010) and IS literature (Burtch et al. 2018). Specifically, we focused on the employment of six housekeeping occupations (Table 2) that may be affected by the entry of TaskRabbit. Second, we acquired data on the entry times of TaskRabbit into different MSAs in the United States from the TaskRabbit official website and news articles[13] (See details in Tables A1 and A2 in Online Appendix A). Third, we gathered data about demographic and socioeconomic covariates at the MSA-year level, such as population, density, education, and income, from the American Community Survey. Lastly, we sourced local establishment data from the U.S. County Business Patterns (CBP) to explore local entrepreneurial activities. The CBP data set provides annual subnational economic data by industry and MSA, and it has widely been used in extant IS research (Kim and Hann 2019). Details of the above data sources are presented in Table A3.

We merged and aggregated these data into an MSA-occupation-year level panel data set containing 24,360 observations covering 267 MSAs[14] and six housekeeping occupations[15] that were consistently identified in the 14-year panel period from 2005 to 2018.[16] We used MSAs as the geographic units for analysis because TaskRabbit typically entered a broad region (e.g., LA metro), instead of a single city, and labor usually moves within such a region (i.e., MSA) that consists of a city and surrounding communities linked by social and economic factors. Using MSA as the geographic unit can better capture the effect of TaskRabbit entry on local employment. To ensure consistency in geographical coverage for the analysis, we mapped the cities where TaskRabbit entered the corresponding MSAs using the city-MSA crosswalk from the Bureau of Labor Statistics.[17] Accordingly, our treatment, TaskRabbit entry, is recorded at the MSA-year level.[18] Finally, we included the occupation levels to account for the effects of occupational characteristics on local employment.[19] As defined earlier,[20] housekeeping occupations are classified into two groups: (i) low-skilled workers (e.g., janitors) and (ii) middle-skilled workers (e.g., first-line managers).

4.2. Variable Definitions

4.2.1. Dependent Variables. The main dependent variables are the *number* and *wage* of incumbent housekeeping workers per MSA_i, $occupation_j$, and $year_t$, using the IPUMS data set. Notably, we focus on the workers with work-for-wages employment status. The unit of annual wage is in 2016 dollars. To study the labor movements after TaskRabbit entry, we also included two groups of dependent variables: (i) indicators of whether an individual worker changed employment status to unemployment, skill-related other occupations, or self-employment using data from Annual Social and Economic Supplement (ASEC) and (ii) the number of housekeeping establishments (in different sizes) using County Business Patterns.

4.2.2. Independent Variables. Our main independent variable is a dichotomous indicator, $TaskRabbit_{it}$, which equals one if TaskRabbit has operated in MSA_i in $year_t$ and otherwise zero. Specifically, for any year t, the MSAs that TaskRabbit has entered are in the treatment group, and all other MSAs without TaskRabbit entry are in the control group. Along with the staggered TaskRabbit entry, the treatment and control groups are updated over time. To explore the differential effects of TaskRabbit on incumbent workers at distinct skill levels (Table 2), we include a moderator, $Manager_j$, which equals one if the housekeeping occupation belongs to the middle-skilled category and otherwise zero.

4.2.3. Location-Specific Time-Varying Covariates. Following existing studies on local employment and online gig platforms (Berger et al. 2018), we included several groups of covariates that potentially influence TaskRabbit entry and local housekeeping employment. First, we controlled for the demographic and socioeconomic conditions of each MSA-year, including total population, the ratio of the population aged above 65 years, the gender ratio in the population, the population share in the labor force, and gross domestic product (GDP). Second, we controlled for the average education attainment for each MSA-year, measured by the population share with a bachelor's degree or higher. Third, we accounted for the potential demand for TaskRabbit services using Google Trends of local searches related to TaskRabbit. The key variables, their definitions, and summary statistics are presented in Table 3.

4.3. Empirical Models and Results for Main Effects (Hypothesis 1 and Hypothesis 2)

We employed a staggered DiD framework with two-way fixed effects to estimate the impact of TaskRabbit entry on local incumbent housekeeping employment (Hypothesis 1), following several IS studies on the impact of online gig platforms (Burtch et al. 2018, Brynjolfsson et al. 2019). In our setting, DiD estimation compares the changes in the employment of incumbent workers in traditional housekeeping businesses, before and after TaskRabbit entry, with the changes in the untreated location over the same period. The weighted[21] OLS estimation is given by the following specification:

$$ln(Y_{ijt}) = \alpha_i + \gamma_j + \theta_t + \beta_1 TaskRabbit_{it} + \boldsymbol{X}_{it}'\beta_2 + \lambda_i t + \delta_i t^2 + \varepsilon_{ijt}, \quad (1)$$

where $ln(Y_{ijt})$ represents the log-transformed number and average annual wage of incumbent housekeeping workers in MSA i, occupation j, and year t. Note that freelance workers and independent contractors working for online gig platforms like TaskRabbit are not included in Y_{ijt} because they do not have a work-for-wages employment status; α_i, γ_j, and θ_t refer to MSA, occupation, and time fixed effects, respectively, to account for their unobserved heterogeneity. $\boldsymbol{X}_{it}$ is a vector of covariates described above for MSA j and year t (Table 3). These covariates are used to account for MSA-year level time-varying heterogeneity. We also included MSA-specific linear ($\lambda_i t$) and quadratic time trends ($\delta_i t^2$) to allow for a unique trajectory of potential socio-economic and regulatory patterns within each MSA over the sample period, further capturing the time-varying unobserved heterogeneity that may

Table 3. Key Variables, Definitions, and Descriptive Statistics

Variable (1)	Definition (2)	Mean (3)	Standard deviation (4)	Minimum (5)	Maximum (6)
Dependent variables					
Total housekeeping					
ln (number of workers)	Log transformed total number of workers	6.75	1.58	1.95	12.25
ln (average wage)	Log transformed average annual wage of workers	9.87	0.61	4.10	13.10
Middle-skilled housekeeping					
ln (number of workers)	Log transformed total number of middle-skilled workers	5.67	1.21	1.95	9.91
ln (average wage)	Log transformed average annual wage of middle-skilled workers	10.30	0.55	5.16	13.10
Low-skilled housekeeping					
ln (number of workers)	Log transformed total number of low-skilled workers	7.20	1.50	2.30	12.26
ln (average wage)	Log transformed average annual wage of low-skilled workers	9.69	0.54	4.10	12.28
Independent variables					
TaskRabbit	An indicator of whether MSA is entered by the TaskRabbit	0.044	0.204	0	1
Manager	An indicator of whether an occupation is a first-line supervisor or manager occupation	0.291	0.454	0	1
Control variables					
Population	Log transformed total population	13.11	1.12	11.41	16.82
Density	Log transformed density	5.50	0.92	1.87	8.01
Income	Log transformed per capital income	10.65	0.198	10.00	11.69
Education	% Population with a bachelor's degree or higher	27.41	7.91	10.10	55.20
Sex Ratio	Males per 100 females	96.83	3.98	86.60	140
Age Ratio	The population not in the labor force divided by that in the labor force (15–64) and multiplied by 100	61.00	8.28	36.60	109.10
Platform service demand	The Google search intensity of TaskRabbit by MSA-year	−0.02	1.01	−1.17	3.08
GDP	Log transformed GDP level by MSA-year.	16.77	1.20	14.81	21.16

Notes. All dependent variables are at the occupation, MSA, and year level. The treatment variable, TaskRabbit, is at the MSA and year level. Manager is at the occupational level. All the control variables are at the MSA and year level.

correlate with housekeeping demand changes within individual MSAs. We clustered standard errors at both the levels of MSA and year.[22]

To empirically examine the differential effects of TaskRabbit entry on housekeeping workers with distinct skill levels (Hypothesis 2), we included an interaction term between the TaskRabbit entry and manager occupations (i.e., middle-skilled workers), as in Equation (2):

$$ln\,(Y_{ijt}) = \alpha_i + \gamma_j + \theta_t + \beta_3 TaskRabbit_{it} + \beta_4 TaskRabbit_{it} \times Managers_j + \mathbf{X}_{it}{}'\beta_5 + \lambda_i t + \delta_i t^2 + \varepsilon_{ijt}. \quad (2)$$

Table 4 presents the main results. In column 1, we find that the TaskRabbit entry is statistically significantly associated with a decline in the number of incumbent workers by 7.1% ($=100 \times (e^{-0.074} - 1)\%$, $p < 0.001$),[23] suggesting that online gig platform entry reduces the supply of incumbent workers in housekeeping occupations. This translates into a reduction of approximately 1,175 incumbent workers per occupation and per year in each MSA following the entry of TaskRabbit.[24] Yet, the effects of TaskRabbit on wages are not statistically significant (column 3). The results support the effect on number (i) but not for wages (ii).

Column 2 in Table 4 shows the differential effects of TaskRabbit entry on incumbent workers at distinct skill levels. Specifically, the coefficients (β_3) for the *TaskRabbit* alone represent the effects of TaskRabbit entry on low-skilled workers, whereas the combination ($\beta_3 + \beta_4$) of *TaskRabbit* and the interaction term *TaskRabbit* × *Manager* (i.e., $0.035 - 0.323 = -0.288$) captures the effects of TaskRabbit entry on middle-skilled workers. As seen, the effect on low-skilled workers is statistically insignificant ($p = 0.215 > 0.1$). For middle-skilled workers, as the results do not directly provide the statistical significance, we used the Wald test with the null hypothesis that the sum of the coefficients (i.e., -0.284) equals zero. The F statistic equals 38.59 ($p < 0.000$), suggesting the TaskRabbit effect on the

Table 4. Difference-in-Differences Estimation of TaskRabbit on Local Housekeeping Employment

	Dependent variables			
	ln(Number of Workers)		*ln(Average Wage)*	
	(1)	(2)	(3)	(4)
TaskRabbit	−0.074**	0.035	0.014	0.014
	(0.020)	(0.026)	(0.033)	(0.036)
TaskRabbit × Manager		−0.323***		−0.002
		(0.062)		(0.028)
Population	0.060	0.059	−0.062	−0.062
	(0.136)	(0.136)	(0.107)	(0.107)
Density	0.056	0.056	0.055	0.055
	(0.063)	(0.063)	(0.123)	(0.123)
Income	−0.154	−0.151	0.468	0.468
	(0.440)	(0.439)	(0.284)	(0.284)
Education	-0.018^{+}	-0.018^{+}	0.007	0.007
	(0.009)	(0.009)	(0.009)	(0.009)
Gender Ratio	0.003	0.003	0.002	0.002
	(0.005)	(0.005)	(0.011)	(0.011)
Age Ratio	−0.009	−0.009	0.003	0.003
	(0.009)	(0.009)	(0.008)	(0.008)
Platform Service Demand	−0.008	−0.008	−0.003	−0.003
	(0.017)	(0.017)	(0.019)	(0.019)
GDP	−0.085	−0.086	−0.264	−0.264
	(0.322)	(0.321)	(0.279)	(0.279)
Year fixed effects	Yes	Yes	Yes	Yes
MSA fixed effects	Yes	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes	Yes
Location-specific time trends	Yes	Yes	Yes	Yes
No. of observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.900	0.900	0.300	0.300

Note. Robust standard errors (clustered at both MSA and year level) in parentheses.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

supply of middle-skilled workers is negative and significant, supporting Hypothesis 2a (i). Yet, no evidence suggests that TaskRabbit entry affects the wages of incumbent workers across skill levels (column 4).

In sum, these results demonstrate that the introduction of TaskRabbit mainly substitutes first-line managers and supervisors in local housekeeping occupations. In other words, incumbent middle-skilled workers, rather than low-skilled ones, are more disrupted after the gig platform entry. As theorized in Hypothesis 2a, this effect may be due to the overlap between the tasks of middle-skilled managerial occupations[25] (i.e., matching housekeeping demand and labor supply, scheduling, and supervising services) and the functions facilitated by TaskRabbit. Interestingly, TaskRabbit entry does not significantly affect the wages of managers,[26] despite a decline in their employment. This might suggest a decrease in market demand for incumbent middle-skilled workers, when TaskRabbit automates part of their managerial tasks.

Notably, the TaskRabbit entry effect on the number and wages of low-skilled workers is statistically insignificant, suggesting that the supply of incumbent low-skilled workers remains unaffected by the gig platform's entry. This null effect might stem from several factors. First, although online gig platforms may attract low-skilled workers, the gap may be filled by new workers entering these positions due to increased market efficiency. Second, low-skilled workers may not leave their current positions because online gig platforms primarily replace middle-skilled workers, and low-skilled workers have less incentive to move. Additionally, although online gig platforms may provide new earning opportunities, they could also drive down service prices by reducing search costs. This might result in no significant change in employment or wage levels for incumbent low-skilled workers.

4.4. Empirical Model and Results for the Labor Redistribution Effect (Hypothesis 3)

We explore labor redistribution mechanisms of gig platforms entry, which may help explain the observed main effects. We collected data from the ASEC of the U.S. Current Population Survey.[27] This data are based on annual surveys of more than 75,000 U.S. households that capture individual-level information, including occupations and employment status in both previous and current calendar years. We collected all observations that belong to middle-skilled and low-skilled workers in the housekeeping occupations in the preceding year, allowing us to code changes in their employment status for the focal year.

Hypotheses 3a, 3b, and 3c proposed three plausible and competing labor movements for housekeeping workers: (i) unemployed, (ii) employed in skill-related occupations,[28] and (iii) self-employed in housekeeping jobs. Accordingly, our three distinct dependent variables denote whether a worker changes from her current work-for-wages employment status in housekeeping occupations to the above three employment modes. We employ a linear probability model (LPM)[29] below to estimate the effects of TaskRabbit entry on the choices of individual housekeeping workers (middle- or low-skilled) to change their employment status:

$$Y_{kitf} = \alpha_i + \theta_t + \beta_1 TaskRabbit_{it} + \boldsymbol{X}_{it}'\beta_2 + \lambda_i t + \delta_i t^2 + \varepsilon_{kitf}, \tag{3}$$

where Y_{kitf} denotes the employment status f for the individual k, in MSA i, and year t; α_j and θ_t refer to the location and time fixed effects, respectively, to account for their unobserved heterogeneity. Similar to the main estimation in Equations (1) and (2), we include a vector of MSA-year level time-varying covariates ($\boldsymbol{X}_{it}$) and MSA-specific linear ($\lambda_i t$) and quadratic time trends ($\delta_i t^2$).

The results are shown in Table 5. For middle-skilled workers (in Panel A), column 1 shows that TaskRabbit entry statistically significantly lowers the probability of their transition from work-for-wages employment to unemployment status (i.e., −2.9%, $p < 0.05$), whereas column 2 shows no significant evidence of them moving to other skill-related (but nonhousekeeping) occupations. These imply that the unemployment effect" (Hypothesis 3a) and the relocation effect (Hypothesis 3b) for incumbent middle-skilled workers are less likely. In column 3, we observe a statistically significant increase in the probability of middle-skilled workers moving from work-for-wages employment status in traditional companies to self-employment in the same housekeeping occupations (i.e., 6.9%, $p < 0.05$), supporting the self-employment effect (Hypothesis 3c) for incumbent middle-skilled workers. For low-skilled workers (in Panel B), no evidence shows any significant changes in their employment. This further supports that online gig platforms may not redistribute the incumbent low-skilled labor force.

Beyond estimating employment status changes at the individual worker level, we explored the effects of TaskRabbit entry on the overall number of workers in unemployment, housekeeping-related jobs, and self-employment in the housekeeping industry using aggregate MSA-year level data, and the results remain consistent (Table C7 in Online Appendix C). To gain a more nuanced understanding of the self-employment effect (Hypothesis 3c), we further decomposed the self-employed status into two categories: (i) self-employed *incorporated* and (ii) self-employed *unincorporated*. Extant studies suggest that self-employed incorporated workers are more likely to be entrepreneurs who start their own businesses, whereas self-employed unincorporated workers are more like freelancers or independent contractors who work on their own (Levine and Rubinstein 2020).

We empirically examine the online gig platform entry effect on these two self-employment types to learn more about where incumbent middle-skilled workers are moving to after TaskRabbit entry. Table 6 shows that TaskRabbit entry is positively and statistically significantly associated with incumbent middle-skilled workers becoming self-employed incorporated (0.027, $p < 0.05$) instead of self-employed unincorporated ($p > 0.1$). This indicates that middle-skilled workers (who might have left their work-for-wages employment position)

Table 5. LPM Estimated Effects of TaskRabbit Entry on Workers' Changed Employment Statuses

	Dependent variables: *Whether an incumbent housekeeping worker (middle-skilled or low-skilled) changed status from work-for-wages employment to the following (1/0)*		
	(1) Unemployed	(2) Employed in skill-related occupations	(3) Self-employed in housekeeping occupations
	Panel A: Middle-skilled worker		
TaskRabbit	−0.029**	0.000	0.069**
	(0.011)	(0.046)	(0.019)
	Panel B: Low-skilled worker		
TaskRabbit	−0.001	−0.003	−0.002
	(0.002)	(0.008)	(0.003)
Time-varying covariates	Yes	Yes	Yes
MSA and year fixed effects	Yes	Yes	Yes
Location-specific time trends	Yes	Yes	Yes

Notes. Examples of skill-related occupations include first-line supervisors of security and administrative support workers (Online Appendix B). Time-varying covariates include all the variables in Table 4. Robust standard errors (clustered at MSA and year) in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$.

Table 6. LPM Estimated Effects of TaskRabbit Entry on Self-Employed Workers' Statuses

	Dependent variables: *Whether an incumbent middle-skilled housekeeping changed status to the following type of self-employment (1/0)*	
	(1) Self-employed incorporated	(2) Self-employed unincorporated
TaskRabbit	0.027*	0.002
	(0.014)	(0.006)
Time-varying covariates	Yes	Yes
Year and MSA fixed effects	Yes	Yes
Location-specific time trends	Yes	Yes
No. of observations	3,465,711	3,465,711
Adjusted R^2	0.114	0.139

Notes. Time-varying covariates include all the variables in Table 4. Robust standard errors (clustered at MSA and year) in parentheses. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$.

tend to start their own housekeeping startups as entrepreneurs after TaskRabbit entry rather than working as freelancers or independent workers.

Next, we take another approach to validate the self-employment effect (Hypothesis 3c) by estimating the changes in the distribution of local housekeeping businesses after TaskRabbit entry. We collected and compiled a longitudinal data set on the number, sizes, locations, and industries of establishments from U.S. County Business Pattern (see Online Appendix C) and replicated the baseline DiD model (Equation (1)) using the number of housekeeping establishments of different sizes for each MSA-year as dependent variables. From Table 7, we observe a significant increase in the total number of local housekeeping establishments following TaskRabbit entry (column 1). More importantly, the increase is mainly driven by the significant increase in small-sized establishments with employment sizes smaller than 50 (columns 2–5), rather than larger establishments with employees larger than 50 (columns 6–9). Together with Tables 5 and 6, this additional evidence of distributional changes in housekeeping businesses further corroborates the self-employment effect that incumbent middle-skilled workers are redistributed to engage more in local (incorporated) entrepreneurial activities, albeit at a small business scale, after the entry of gig platforms.

In addition to the labor movements hypothesized and tested above, we examined a set of alternative labor movement possibilities (Figure C1, Online Appendix C), such as transitions from middle-skilled housekeeping occupations to low-skilled ones and vice versa. Yet, no evidence supports such movements (Tables C3–C6), lending more credence to the self-employment movement of incumbent middle-skilled workers (Hypothesis 3c) as the primary labor redistribution mechanisms to explain the effect of gig platform entry.

To delve deeper into the theoretical mechanisms, we investigated which company sizes are most affected by TaskRabbit. Should TaskRabbit enhance operational efficiency, smaller companies would be more impacted due to their higher incentive to adopt online gig platforms and simpler task management. We found that workers employed by small companies are indeed significantly more likely to leave their companies, following TaskRabbit entry, compared with workers in large firms (Table E1, Online Appendix E), supporting our hypothesis. Additional analysis shows that TaskRabbit's entry significantly reduces working hours for middle-skilled workers (Table E2, Online Appendix E),

Table 7. DiD Estimated Effects of TaskRabbit Entry on Number of Local Housekeeping Establishments

	Dependent variables: *ln(# establishment of different employment sizes)*								
	Total (1)	1–4 (2)	5–9 (3)	10–19 (4)	20–49 (5)	50–99 (6)	100–249 (7)	250–499 (8)	500–999 (9)
TaskRabbit	0.056***	0.079***	0.043*	0.047**	0.039*	−0.014	−0.024	−0.093	−0.076
	(0.015)	(0.020)	(0.024)	(0.023)	(0.022)	(0.029)	(0.046)	(0.069)	(0.102)
Time-varying covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and MSA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	4,014	3,434	3,913	3,825	3,647	2,806	2,162	1,012	641
Adjusted R^2	0.997	0.994	0.981	0.978	0.979	0.951	0.941	0.892	0.864

Notes. Columns 2–9 report the effect of TaskRabbit entry on the number of establishments of different sizes, starting from those with one to four workers. Time-varying covariates include all the variables in Table 4. Robust standard errors (clustered at MSA and year level) in parentheses. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$.

Table 8. Summary of Robustness Tests for the Baseline Results

Empirical concern	Test	Finding	Location
Validity of DiD estimator	1. Check parallel trends using a relative time model 2. Check reverse causality using a discrete-time hazard model (logit hazard model) 3. Check time-varying confounders by running a random implementation test	Pass	Tables D1 and D2, Figure D1
Sample selection	1. Coarsened Exact Matching for MSAs 2. Only include treated MSAs 3. Only include large MSAs 4. Exclude MSAs that entered after 2017	Consistent	Tables D3–D8
Enhanced identification strategy	1. Heterogeneity-Robust DiD Model 2. Generalized Synthetic Control	Consistent	Tables D9–D11, Figures D2–D3
Impact of other platforms	1. Related platforms overview 2. Include main competitors (Handy.com) 3. Exclude workers in traveler accommodation industry	Consistent	Tables D12–D18
Other robustness checks	1. Linear time trend 2. Alternative measures for TaskRabbit 3. Lagged effects of TaskRabbit 4. Moderating role of housekeeping share 5. Confidence interval of the estimation range	Consistent	Tables D19–D23

further corroborating its role in improving operational efficiency and reducing reliance on these workers.

4.5. Robustness Checks

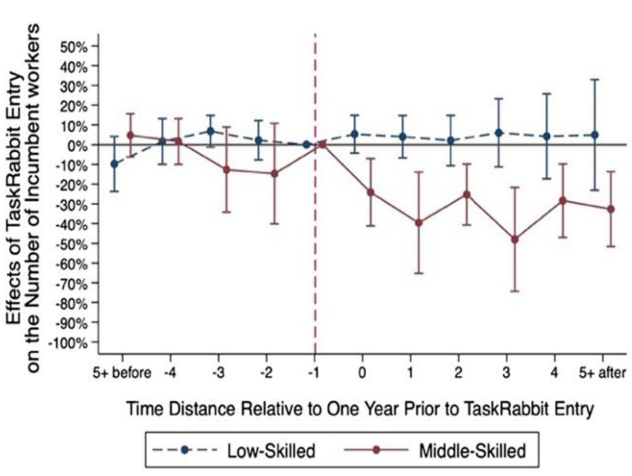
Next, we perform a battery of robustness tests on our main findings (see Table 8 for a summary).

4.5.1. Validity of the Baseline DiD Estimates. We start with checking the validity of our baseline DiD estimates. First, we examined the parallel trends assumption—no difference in the pretreatment trends between TaskRabbit-treated and untreated locations. Following the labor economics and IS literature (Autor 2003, Chan and Ghose 2014), we included a set of dummy variables to indicate the relative temporal distances between a given year and the TaskRabbit entry years. Results are presented in Figure 1 (also in Table D1, Online Appendix D). As seen, no statistically significant differences exist for the number of middle-skilled and low-skilled workers between treated and untreated MSAs before TaskRabbit entry, supporting the parallel trends assumption.

Second, TaskRabbit entry in the focal year might be determined by the trends in the employment trends of the local housekeeping industry in the past few years, giving rise to a reverse causality concern. Following the literature (Cheng et al. 2020), we used a hazard logit model to predict TaskRabbit entry using past local employment in housekeeping occupations with one year, two years, and three years prior to TaskRabbit entry and other time-varying covariates at the MSA-year level. The results show that past employment and wage trends do not predict TaskRabbit entry (see Table D2, Online Appendix D), suggesting that reverse causality may not be a serious concern in our study.

Third, the observed effect might be picked up due to a natural downward trend in the demand for middle-skill managers in the housekeeping industry rather than the effect of TaskRabbit entry. To check this possibility, we conducted a permutation test. Specifically, we randomly assigned placebo treatments across locations and times and replicated the main model (Equation (1)) 1,000 times. We plotted the distribution of the coefficients of $TaskRabbit_{it} \times Managers_j$ (Figure D1,

Figure 1. (Color online) DiD Estimated Effects of Leads and Lags of TaskRabbit Entry over Time



Note. Error bars depict 95% confidence intervals of the point estimates.

Online Appendix D) and found the mean of placebo treatment effects does not deviate from zero, let alone significantly different from our DiD estimates in Table 4, indicating that the observed effects of TaskRabbit entry were not spurious.

4.5.2. Sample Selection. It might be possible that the untreated MSAs in our sample are not a perfect counterfactual for the treated ones. We conducted several subsample analyses to alleviate this concern. First, we used coarsened exact matching to balance the covariates between treated and untreated MSAs and replicate the analysis using matched MSAs (Tables D3 and D4, Online Appendix D). Second, considering that treated and untreated locations may follow different employment trends, we replicated the analysis using a subsample in which only treated MSAs are included (Table D5, Online Appendix D). Third, to account for TaskRabbit's tendency to enter big cities, given their accumulation of housekeeping demand, we replicated the analysis by only including the top 50 MSAs with large populations (Table D7, Online Appendix D). Finally, to alleviate the impact brought by the acquisition from IKEA in 2017, we excluded all samples after 2017 and replicated the analysis (Table D8, Online Appendix D). In each of the above cases, results remained consistent with our baseline DiD estimates.

4.5.3. Enhanced Identification Strategies. While our results have been consistent thus far, the standard DiD model may face limitations, such as the staggered entry setting and imperfect counterfactuals. To address these concerns, we enhanced our identification strategy with two approaches: heterogeneity-robust DiD and generalized synthetic control.

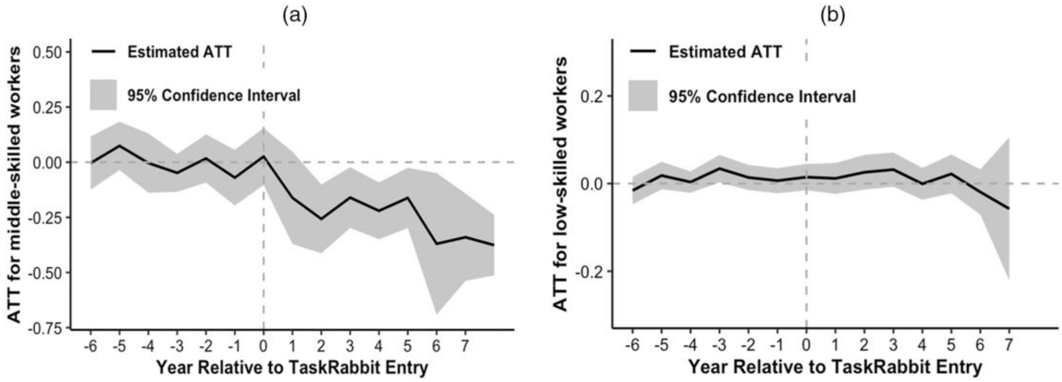
4.5.3.1. Heterogeneity-Robust DiD Model. Recent studies have suggested that the standard DiD model may lead to a biased estimation with staggered treatment timing (Baker et al. 2022). Specifically, the standard DiD model generates many different comparison groups between a treatment and a control group. Studies suggest that the estimations may be problematic when comparing the earlier adopters with the late adopters and when there exists a dynamic treatment effect (Goodman-Bacon 2021).

Following the econometric remedies provided by these studies, we first performed Bacon decompositions to decompose our treatment effect into groups based on different controls (i.e., never treated, earlier adopters, and late adopters). Then, we used the estimator from Callaway and Sant'Anna (2021) to address the concern by first estimating the individual cohort-time-specific treatment effects and then aggregating these effects together. Results from Bacon decompositions suggest that the observed negative employment effects are consistent across different control groups (Figure D2 and Table D9, Online Appendix D). The analysis using Callaway and Sant'Anna (2021) shows consistent estimates with our baseline results, supporting our main findings on the employment effects of TaskRabbit entry (Table D10).

4.5.3.2. Generalized Synthetic Control. To address the concern about time-varying confounders due to the imperfect control group, we employed a generalized synthetic control (GSC) approach (Xu 2017), which is the combination of a synthetic control model (Abadie 2021) and an interactive fixed-effect model (Bai 2009). The synthetic control model constructs a weighted combination of untreated MSAs (i.e., synthetic controls) that closely resembles the covariates and outcome of the treated MSAs in the pretreatment periods, which naturally satisfies the parallel trend assumption. Accordingly, the trends of control and treated groups should be very close in the pretreatment periods, and the differences in employment during the posttreatment periods should be solely driven by the treatment per se (i.e., TaskRabbit entry). The interactive fixed-effect model includes a linear and additive latent factors component to capture any unobservable time-varying confounders (Bai 2009). Results indicate that the effect of TaskRabbit entry on the number of housekeeping managers (middle-skilled workers) is negative and statistically significant ($\beta = -0.146$, $p < 0.01$), whereas that for low-skilled workers is not significant ($p = 0.48 > 0.1$) (Table D11, Online Appendix D). Figure 2 visually shows the treatment effect over time. As seen, the number of middle-skilled incumbent workers decreases significantly after TaskRabbit entry. However, the treatment effect of low-skilled incumbent workers remains statistically indifferent from zero. In sum, the GSC results yet again corroborate our main findings.

4.5.4. Role of Other Online Gig Platforms. While our empirical focus is on TaskRabbit, one of the largest and earliest platforms of housekeeping services, it is crucial to acknowledge the presence of similar gig platforms in the market, such as Handy and Thumbtack, which may potentially influence our observed effect of TaskRabbit. To address this concern, first, we conducted a detailed survey of all major competitors of TaskRabbit (Table D12, Online Appendix D) and ruled out the platforms that had minimal impacts on our results. Second, we focused on one major competitor—Handy—which shares comparable staggered expansion history and size with TaskRabbit. Specifically, we incorporated the Handy entry effect in our baseline model. We still observe a consistent and significant downward trend in the number of managers following both the Handy entry and TaskRabbit entry (Table D14, Online Appendix D). Furthermore, although Thumbtack matches

Figure 2. GSC Estimated Effects of TaskRabbit on the Number of Housekeeping Workers



Notes. (a) Middle-skilled workers. (b) Low-skilled workers.

TaskRabbit in size, it differs in matching processes and service range. To account for Thumbtack's potential effect, we used its Google Trends search intensity as a proxy, and the results remained consistent (Table D15, Online Appendix D). Finally, we replicated the baseline estimation using the number of platforms entering MSAs as a proxy for treatment intensity, yielding similar and consistent patterns with our main findings (Table D16, Online Appendix D).

5. Discussion and Conclusion

5.1. Summary of Key Findings

Online gig platforms have substantially reshaped the U.S. labor markets by reducing search costs (Chen and Horton 2016, Goldfarb and Tucker 2019) and granting workers flexibility and autonomy (Burtch et al. 2018). However, there remains a dearth of analysis and evidence to elucidate the labor movement amid the rise of the online gig economy. To bridge this gap, we study the interplay between the emergence of online gig platforms and local employment in housekeeping occupations. Exploiting the expansion pattern of TaskRabbit across the United States, we identify a statistically significant downward trend in incumbent housekeeping employment after the online gig platform (TaskRabbit) entry. Further, we delve into the effect heterogeneity across incumbent housekeeping workers at distinct skill levels—low-skilled workers (i.e., cleaners or janitors) and middle-skilled workers (i.e., first-line managers or supervisors). Our findings reveal that the overall decrease in housekeeping employment is mainly driven by a disproportionate decline of incumbent middle-skilled workers after TaskRabbit entry, whereas low-skilled workers remain largely unaffected during the same period. These results suggest that online gig platforms may replace managerial workers whose cognitive tasks overlap with the algorithmic functions of the online gig platform, such as matching and supervising services. This also explains why low-skilled incumbent workers are less impacted, as their primary tasks (manual and labor-intensive) are unlikely to be automated and replaced by online gig platforms, at least in their current form.

To probe into the movement of incumbent middle-skilled workers, we hypothesize and test different possibilities of labor redistribution: Online gig platforms, like TaskRabbit, could drive the transition of housekeeping workers toward self-employment within the same industry, unemployment, or employment in skill-related occupations in other industries. Interestingly, our empirical evidence only supports the "self-employment" explanation, and the self-employment redistribution is mainly driven by the observed transition of incumbent middle-skilled workers toward becoming small business owners (incorporated and entrepreneurial roles) instead of becoming freelancers or independent workers (unincorporated roles). Integrating these empirical insights, our study suggests that online gig platforms cannot be simplistically characterized as skill biased (against middle-skilled, albeit not low-skilled workers). Instead, they may facilitate the redistribution of the middle-skilled labor force toward self-employment, thereby fostering local entrepreneurial activities. This labor redistribution mechanism offers novel and nuanced insights into the role of online gig platforms in local labor markets and employment dynamics.

5.2. Contributions to Theory and Research

This study makes notable contributions to the evolving theory and research on the gig economy and the interplay between technology and employment. First, this study enriches the burgeoning literature on the labor implications of online gig platforms (Berger et al. 2018, Burtch et al. 2018, Li et al. 2021). Extant studies have debated the role of these platforms on local labor markets, often presenting competing theories and relying mostly on anecdotal evidence (Fraiberger and

Sundararajan 2017, Schor 2017, Schwellnus et al. 2019). Our study situates this debate within a typical service occupation, proposing hypotheses on the disruptive effects of online gig platforms on incumbent employment. Through rigorous analysis and robust empirical evidence, we reconcile the competing theoretical and anecdotal predictions. More importantly, we move beyond the simplistic binary view of labor effect of technology (complementarity versus substitution) in the popular press and academic research, unraveling a nuanced mechanism that elucidates how online gig platforms shift incumbent workers toward self-employment and potential engagement in local entrepreneurial opportunities.

Second, this study contributes to the gig platform literature by demonstrating the heterogeneous effects of platform entry on workers at distinct skill levels (i.e., middle-skilled versus low-skilled). Recent scholarship on online gig platforms has extensively centered on cases like Uber and Airbnb and mainly studied their socioeconomic impact rather than investigating whether and how online gig platforms are skill-biased and their disproportionate effects across workers with different skills. TaskRabbit's service coverage and the unique skill structure inherent in traditional housekeeping occupations allow us to take a closer examination of the employment effect heterogeneity among different skilled workers groups and to better understand how and why this heterogeneity emerges amid the proliferation of online gig platforms.

Third, this study adds to the emerging discourse on digital platforms and online gig work. Specifically, the literature has mainly focused on offshoring information-based virtual jobs on global platforms (e.g., Freelancer, Upwork, Mechanical Turk), often devoid of geographic constraints (Hong and Pavlou 2017). Our research extends the literature to examine *location-based* gig platforms that match service demand and supply online but require *offline* physical work (Blinder 2009). Notably, the workers we focus on in this study are *not* freelancers (independent workers) working for online gig platforms, but they are mainly incumbent workers in traditional businesses whose employment prospects may be disrupted or altered by the advent of online gig platforms that automate their routine cognitive work tasks.

Finally, our study extends SBTC theory by examining the impact of a new technological innovation, *online gig platforms*, on local labor markets. SBTC has been a dominant hypothesis in labor economics, implying that technology is positively biased toward highly skilled workers by increasing their relative productivity while substituting low-skilled workers. While previous SBTC research has mainly focused on general-purpose technologies, such as computers in the workplace, our study broadens the scope to include online gig platforms. These platforms disrupt service occupations by facilitating a more efficient matching, promoting a more flexible work style, and reducing barriers to self-employment. Our empirical findings indicate a decreased demand for middle-skilled workers, with the demand for low-skilled workers unchanged in traditional housekeeping businesses. This aligns with recent developments in STBC theory, particularly the *polariz*ed employment in service occupations (Autor and Dorn 2013), which suggests that technology substitutes routine tasks but complements complex manual tasks that are not easily automated. Upon further exploration, our findings reveal that online gig platforms do *not* necessarily replace middle-skilled workers but instead create job opportunities for them, driving them toward local self-employment activities. This observation is an important empirical support for the recent theoretical work in labor economics, which posits that "technology displaces and reinstates labor" (Acemoglu and Restrepo 2019). In sum, our analysis both echoes and enriches SBTC theory by substantiating the labor redistribution role of online gig platforms, contextualizing SBTC theory within the housekeeping labor markets, and extending the everlasting debate on the intricate interplay between technology, skills, and employment.

5.3. Contributions to Public Policy and Practice

This study has insightful implications for public policy and practice. For policymakers, they must recognize and reconsider the role of online gig platforms in stimulating local labor markets and the economy. Our findings imply that the emergence of online gig platforms, such as TaskRabbit, redistributes workers from traditional businesses to self-employment. This encourages local entrepreneurial activities, albeit in the form of newly established small businesses. Besides, this study engages in the debate on the welfare implications of the gig economy for workers. Online gig platforms typically offer significant autonomy and control over aspects such as setting service prices and defining and supervisory work tasks. It is necessary for regulators to protect workers' conditions, including working hours, wages, and benefits. Although anecdotal claims attribute unfair competition and suppressed wages to online gig platforms, our study does not find major changes in the earnings of incumbent workers in housekeeping occupations, following TaskRabbit entry. However, research with proprietary platform data is needed to thoroughly assess the welfare implications of the gig economy for workers, particularly at lower socio-economic levels.

For practitioners, our findings imply that online gig platforms not only streamline business operations by matching and supervising but also provide middle-skilled workers in traditional companies with opportunities to start their own ventures and participate in the gig economy. This suggests a promising platform launching strategy—targeting and converting skilled workers from traditional businesses into service providers for the gig platform. In doing so, the increase in the service supply side can attract more clients, creating a positive externality and contributing to the ultimate success of the online gig platform. In contrast, the implications for traditional companies may be more concerning. It is critical for these companies to understand the labor implications of online gig platforms, reassess their job designs and the role of technology in the workplace, and proactively adapt their incentive structure and company culture to accommodate the changing needs of workers, such as flexibility and autonomy, given the gig economy.

5.4. Limitations and Future Research

This work has several limitations, which may create opportune directions for future research. First, our empirical evidence is not based on an ideal randomized controlled trial that assigns TaskRabbit to enter locations at random. Yet, conducting such an experiment is rarely possible for a gig platform due to unforeseeable economic costs. To address the nonrandomness of TaskRabbit's entry, we included a comprehensive set of covariates in our main analysis to account for potential confounders. Importantly, our estimates are consistently validated through a battery of robustness and falsification tests (Table 8). Despite these efforts, we remain cautious in interpreting the observed effects as causal.

Second, we acknowledge that we use only one online gig platform, TaskRabbit, as our empirical focus to illustrate the employment effects of gig platforms on incumbent housekeeping workers, although other platforms exist. A thorough survey helped exclude the effects of many platforms on our estimates, given their size, expansion history, and entry timing (Table D12, Online Appendix D). We incorporated a similar and comparable platform, Handy, into our analysis and found consistent results. Nevertheless, we could not account for every platform due to data constraints. Although a single study cannot guarantee broad generalizability, probing into a theoretical inquiry and situating our study within a typical context serves as a viable means of supporting the ultimate generalizability (Cheng et al. 2016). Our empirical findings support potential *theoretical* generalizability, resonating with recent developments in labor economics (Acemoglu and Restrepo 2019) and IS studies on platforms and entrepreneurship (Burtch et al. 2018).

Third, although online gig platforms can affect a broader range of service occupations, our study only explores one subgroup of them—housekeeping occupations. We argue that the observed effects may apply to other service occupations (e.g., moving services) that share similar tasks with housekeeping occupations. Specifically, middle-skilled workers, whose roles involve tasks like matching and supervising, are more likely to be affected by these platforms than low-skilled workers primarily engaged in manual tasks.

Fourth, we show minimal impact of online gig platforms on the wages of incumbent housekeeping workers, although some subsamples show a negative wage effect on middle-skilled workers (Tables D4 and D18, Online Appendix D). We cannot measure potential earning changes when incumbent middle-skilled workers shift to self-employed due to different income reporting methods for incumbent and self-employed workers.

Finally, while the finding that online gig platforms may promote local entrepreneurial activities is novel and encouraging, it requires further empirical validation. Because of data limitations, we cannot track how many self-employed workers use TaskRabbit for their businesses. If data were available to measure how they use gig platforms, we would have offered a better estimate of the TaskRabbit effect to directly identify all mechanisms involved. Nevertheless, our theorization and supportive evidence open opportunities for future research to test the labor redistribution mechanisms. Additionally, our findings are specific to new businesses in the housekeeping industry and may not apply to other industries.

6. Concluding Remark

This study examines the interplay between the emergence of online gig platforms and local employment in traditional service industries. We find a significant decline in the employment of incumbent middle-skilled (relative to low-skilled) workers, who mainly perform matching/supervising tasks, following gig platform entry. Our empirical exploration challenges a substitution explanation often posited by critics of online gig platforms, but rather it supports a labor redistribution explanation—the rise of online gig platforms shifts middle-skilled workers in traditional businesses to self-employment. Our study, to our knowledge, is among the first to understand the labor implications of online gig platforms through the theoretical lens of SBTC. Our initial evidence suggests that gig platforms are "skill biased," by substituting incumbent middle-skilled workers whose routine tasks heavily overlap with the services offered by gig platforms while having little impact on low-skilled workers who perform manual labor-intensive tasks. Our further in-depth analysis reveals that online gig platforms do not completely replace jobs of incumbent middle-skilled housekeeping workers, but rather they redistribute these workers to self-employment, stimulating local entrepreneurial endeavors. While these findings are theoretically and empirically exciting, the complex discourse on the interplay between online gig platforms and local incumbent employment *cannot* be fully unpacked by a single study. We acknowledge the existence of other gig platforms in similar markets, but our analysis is limited to two major ones (TaskRabbit and Handy). Hence, caution should be exercised in extrapolating our findings to other platforms and occupations. As noted in the commentary on IS research (Hosanagar 2017), we consider our study an example of a "half answer" to the "big question" of the labor implications of online gig platforms. We hope this research sparks scholarly discussion and encourages further theoretical and empirical work to fully understand the broader labor redistribution mechanisms and broader effects of online gig platforms on other occupations, industries, and countries.

Endnotes

[1] *Traditional industries* refer to incumbent businesses that have largely operated independently of online gig platforms.

[2] Examples include the following: https://mhrglobal.com/us/en/blog/gig-economy-good-bad-and-future and https://www.bbvaopenmind.com/en/articles/the-impact-of-the-gig-economy/.

[3] Incumbent workers are employees who work for private employers for wages, salary, commission tips, piece-rates, or pay in kind (i.e., work as employees instead of employers or self-employed workers). Throughout the manuscript, we use work-for-wages and incumbent workers interchangeably to indicate this class of workers.

[4] We use the housekeeping occupation as our empirical instantiation because the tasks involved in housekeeping constitute the main services offered by many emerging gig platforms. Other types of service occupations may also share similar skill levels and be disrupted by gig platforms, such as personal care occupations and transportation moving occupations. See more at https://www.onetcenter.org/dictionary/26.3/excel/related_occupations.html.

[5] Traditional housekeeping businesses may also involve high-skilled (rather than middle- or low-skilled) workers (e.g., CEO and CFO). We excluded these types of workers in our analysis because their occupation codes do not belong to housekeeping occupations. Their skills and tasks can be applied to a wide range of businesses but not exclusive to housekeeping businesses.

[6] Per Autor and Dorn (2013), the skill percentile is measured by the U.S. mean occupational wage in 1980. Routine-intensive occupations (e.g., first-line managers) tend to fall in the middle of the distribution (thereby being classified as the middle-skilled), whereas manual-intensive occupations (e.g., cleaners) tend to be at the bottom of the distribution (thereby low-skilled).

[7] Because of data constraints, we could not observe changes in wages for those middle-skilled workers who changed the employment status from work-for-wages employment to self-employment status.

[8] Anecdotes suggest the costs of opening self-employed businesses: https://www.businessnewsdaily.com/5-small-business-start-up-costs-options.html and https://www.bizjournals.com/bizjournals/how-to/growth-strategies/2015/07/how-to-build-a-strong-network-of-customers.html.

[9] See https://support.taskrabbit.com/hc/en-us/articles/204411070-What-s-Required-to-Become-a-Tasker.

[10] See https://www.forbes.com/sites/tracybrower/2022/09/11/what-its-really-like-to-be-a-gig-worker/?sh=7078aaed6507.

[11] For instance, a Pew Research survey indicates that around 70% of gig platform workers maintain their current jobs and use online gig platforms as side jobs. See details at https://www.pewresearch.org/internet/2021/12/08/the-state-of-gig-work-in-2021.

[12] IPUMS covers three types of workers: (i) work-for-wages, (ii) the self-employed, and (iii) the unemployed.

[13] See https://www.taskrabbit.com/locations.

[14] We used the MET2013 variable in IPUMS to generate the MSA identifier. MET2013 uses the 2013 definitions for MSAs from the U.S. Office of Management and Budget (OMB). In total, there are 267 MSAs consistently available in the panel from 2005 to 2018. More details at https://usa.ipums.org/usa-action/variables/met2013#description.

[15] The six occupations include two middle-skilled occupations and four low-skilled occupations shown in Table 2.

[16] We did not include the sample before 2005 due to the limited availability of the MSA data in that period.

[17] Accessed at https://www.bls.gov/cew/classifications/areas/county-msa-csa-crosswalk.htm.

[18] We also adjusted the measurement for the treatment variable based on the specific TaskRabbit entry month of a year (i.e., if the entry month is October, November, or December, we recoded the treatment equal to one for the next calendar year). The results are consistent and are available in Online Appendix D.

[19] We replicated the model using the MSA-year level data in the robustness checks, and the results are consistent.

[20] There is a tiny portion of high-skilled workers (e.g., CEOs, CFOs) in housekeeping companies, but because they do not engage in housekeeping-related tasks and are not classified under housekeeping occupations, they are not considered in our analysis.

[21] Following prior studies focusing on geographical areas (Chan et al. 2019), our models are weighted by the area density.

[22] Because there is no variation in the classification of middle-skilled workers in 2005–2018, the direct/main effect of *Managers* is absorbed by occupation fixed effects (and not explicitly estimated) in the DiD model estimation.

[23] By summarizing the coefficients across all model specifications in our paper, estimates range is from −0.041 to −0.095 for total number of workers and is from −0.146 to −0.448 for middle-skilled workers (see details in Table D23, Online Appendix D).

[24] This number is calculated based on the assumption of a constant treatment effect. More details are provided in Online Appendix D.

[25] For examples, please see https://www.onetonline.org/link/summary/37-1011.00.

[26] Notably, when we narrowed our sample to housekeeping workers within the building and dwelling industry (specifically, the primary industry comprising housekeeping workers directly impacted by TaskRabbit), the effect of TaskRabbit entry on the wages of middle-skilled workers is negative and *significant* (see Table D17 in Online Appendix D). Other observed effects remain consistent. These results bolster the notion of a diminished demand for incumbent middle-skilled workers.

[27] See https://www.census.gov/programs-surveys/saipe/guidance/model-input-data/cpsasec.html.

[28] We adopted the skill-related occupations from O*NET data set for both middle-skilled and low-skilled housekeeping workers. A detailed list of related occupations can be found in Online Appendix B. The skill-related occupations are evaluated by experts and are determined by (i) what people in the occupation do, (ii) what they know, and (iii) what they are called (https://www.onetcenter.

org/dictionary/26.3/excel/related_occupations.html). We removed any occupations that may be directly affected by TaskRabbit, such as Material Mover.

[29] We use the linear probability model here to increase the interpretability of coefficients (Caudill 1988).

References

Abadie A (2021) Using synthetic controls: Feasibility, data requirements, and methodological aspects. *J. Econom. Literature* 59(2): 391–425.

Acemoglu D (2002) Technical change, inequality, and the labor market. *J. Econom. Literature* 40(1):7–72.

Acemoglu D, Autor D (2011) Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, vol. 4 (Elsevier, New York), 1043–1171.

Acemoglu D, Restrepo P (2019) Automation and new tasks: How technology displaces and reinstates labor. *J. Econom. Perspective* 33(2):3–30.

Agrawal A, Gans JS, Goldfarb A (2019) Artificial intelligence: The ambiguous labor market impact of automating prediction. *J. Econom. Perspective* 33(2):31–50.

Anderson M, McClain C, Faverio M, Gelles-Watnick R (2021) The state of gig work in 2021. Report, Pew Research Center, Washington, DC.

Autor DH (2003) Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *J. Labor Econom.* 21(1):1–42.

Autor DH, Dorn D (2013) The growth of low-skill service jobs and the polarization of the US labor market. *Amer. Econom. Rev.* 103(5):1553–1597.

Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: An empirical exploration. *Quart. J. Econom.* 118(4):1279–1333.

Bai J (2009) Panel data models with interactive fixed effects. *Econometrica* 77(4):1229–1279.

Baker AC, Larcker DF, Wang CC (2022) How much should we trust staggered difference-in-differences estimates? *J. Financial Econom.* 144(2):370–395.

Barrios JM, Hochberg YV, Yi HL (2020) Launching with a parachute: The gig economy and entrepreneurial entry. Working paper, University of Chicago, Becker Friedman Institute for Economics, Chicago.

Benson A, Sojourner A, Umyarov A (2020) Can reputation discipline the gig economy? Experimental evidence from an online labor market. *Management Sci.* 66(5):1802–1825.

Berger T, Chen C, Frey CB (2018) Drivers of disruption? Estimating the Uber effect. *Eur. Econom. Rev.* 110:197–210.

Berger T, Frey CB, Levin G, Danda SR (2019) Uber happy? Work and well-being in the 'gig economy'. *Econom. Policy* 34(99):429–477.

Blinder AS (2009) How many US jobs might be offshorable? *World Econ.* 10(2):41.

Brynjolfsson E, Hui X, Liu M (2019) Does machine translation affect international trade? Evidence from a large digital platform. *Management Sci.* 65(12):5449–5460.

Brynjolfsson E, Rock D, Syverson C (2018) Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. Agrawal A, Gans J, Goldfarb A, eds. *The Economics of Artificial Intelligence: An Agenda* (University of Chicago Press, Chicago), 23–57.

Burtch G, Carnahan S, Greenwood BN (2018) Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Sci.* 64(12):5497–5520.

Callaway B, Sant'Anna PH (2021) Difference-in-differences with multiple time periods. *J. Econometrics* 225(2):200–230.

Card D, DiNardo JE (2002) Skill-biased technological change and rising wage inequality: Some problems and puzzles. *J. Labor Econom.* 20(4):733–783.

Casey G (2018) Technology-driven unemployment. Retrieved February 25, 2022, https://ideas.repec.org/p/red/sed018/302.html.

Caudill SB (1988) An advantage of the linear probability model over probit or logit. *Oxford Bull. Econom. Statist.* 50(4):425–427.

Chan J, Ghose A (2014) Internet's dirty secret assessing the impact of online intermediaries on HIV transmission. *Management Inform. Systems Quart.* 38(4):955–976.

Chan J, Mojumder P, Ghose A (2019) The digital Sin City: An empirical study of Craigslist's impact on prostitution trends. *Inform. Systems Res.* 30(1):219–238.

Chen DL, Horton JJ (2016) Research note—Are online labor markets spot markets for tasks? A field experiment on the behavioral response to wage cuts. *Inform. Systems Res.* 27(2): 403–423.

Cheng S, Park B (2020) Flows and boundaries: A network approach to studying occupational mobility in the labor market. *Amer. J. Sociol.* 126(3):577–631.

Cheng Z, Dimoka A, Pavlou PA (2016) Context may be King, but generalizability is the Emperor! *J. Inform. Tech.* 31(3): 257–264.

Cheng Z, Pang M-S, Pavlou PA (2020) Mitigating traffic congestion: The role of intelligent transportation systems. *Inform. Systems Res.* 31(3):653–674.

Cramer J, Krueger AB (2016) Disruptive change in the taxi business: The case of Uber. *Amer. Econom. Rev.* 106(5):177–182.

Dixon J, Hong B, Wu L (2021) The robot revolution: Managerial and employment consequences for firms. *Management Sci.* 67(9): 5586–5605.

Einav L, Farronato C, Levin J (2016) Peer-to-peer markets. *Annu. Rev. Econom.* 8:615–635.

Ford M (2015) *Rise of the Robots: Technology and the Threat of a Jobless Future* (Basic, New York).

Fossen FM, Sorgner A (2021) Digitalization of work and entry into entrepreneurship. *J. Bus. Res.* 125:548–563.

Fraiberger SP, Sundararajan A (2017) Peer-to-peer rental markets in the sharing economy. NYU Stern School of Business Research paper, New York.

Frey CB, Osborne MA (2017) The future of employment: How susceptible are jobs to computerisation? *Tech. Forecasting Soc. Change* 114:254–280.

Gatta M, Boushey H, Appelbaum E (2009) High-touch and here-to-stay: Future skills demands in US low wage service occupations. *Sociology* 43(5):968–989.

Goldfarb A, Tucker C (2019) Digital economics. *J. Econom. Literature* 57(1):3–43.

Gong J (2016) A structural two-sided matching model of online labor markets. Fox School of Business Research paper, Philadelphia.

Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. *J. Econometrics* 225(2):254–277.

Hall JV, Krueger AB (2018) An analysis of the labor market for Uber's driver-partners in the United States. *Industry Labor Related Rev.* 71(3):705–732.

Hong Y, Pavlou PA (2017) On buyer selection of service providers in online outsourcing platforms for IT services. *Inform. Systems Res.* 28(3):547–562.

Horton JJ (2017) The effects of algorithmic labor market recommendations: Evidence from a field experiment. *J. Labor Econom.* 35(2):345–385.

Hosanagar K (2017) Senior editor perspectives. *Inform. Systems Res.* 28(4):689–689.

Isaac E (2015) Innovative clusters & new work: A case study of TaskRabbit. Report, Berkeley Roundtable on the International Economy, University of California, Berkeley.

Jenkins ME, Isom B, Koopman C (2023) *Tech-Enabled Gig Jobs: Policy Solutions for the Future of Work* (The Center for Growth and Opportunity, Logan, UT).

Kerr WR, Lincoln WF (2010) The supply side of innovation: H-1B visa reforms and US ethnic invention. *J. Labor Econom.* 28(3): 473–508.

Kim K, Hann I-H (2019) Crowdfunding and the democratization of access to capital—An illusion? Evidence from housing prices. *Inform. Systems Res.* 30(1):276–290.

Krusell P, Ohanian LE, Ríos-Rull JV, Violante GL (2000) Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica* 68(5):1029–1053.

Lazear EP (2004) Balanced skills and entrepreneurship. *Amer. Econom. Rev.* 94(2):208–211.

Levine R, Rubinstein YZ (2020) Selection into entrepreneurship and self-employment. CEP Discussion Paper No. CEPDP1722, London School of Economics and Political Science, Centre for Economic Performance, London.

Li Z, Hong Y, Zhang Z (2021) The empowering and competition effects of the platform-based sharing economy on the supply and demand sides of the labor market. *J. Management Inform. Systems* 38(1):140–165.

Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW (2021) Algorithmic management of work on online labor platforms: When matching meets control. *Management Inform. Systems Quart.* 45(4).

Moscarini G, Vella FG (2008) Occupational mobility and the business cycle. NBER Working Paper No. 13819, National Bureau of Economic Research, Cambridge, MA.

Nandakumar R (2020) Positive spillover effects of Uber on NYC's yellow taxis. Report, Srini Raju Centre for IT and the Networked Economy, Hyderabad, India.

Rayle L, Dai D, Chan N, Cervero R, Shaheen S (2016) Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transportation Policy* 45:168–178.

Robinson C (2018) Occupational mobility, occupation distance, and specific human capital. *J. Human Resources* 53(2):513–551.

Ruggles S, Flood S, Goeken R, Grover J, Meyer E, Pacas J, Sobek M (2019) *IPUMS USA: Version 9.0 [data set]* (IPUMS 10:D010, Minneapolis, MN).

Schor JB (2017) Does the sharing economy increase inequality within the eighty percent?: Findings from a qualitative study of platform providers. *Cambridge J. Regions Econom. Soc.* 10(2): 263–279.

Schor JB, Attwood-Charles W, Cansoy M, Ladegaard I, Wengronowitz R (2020) Dependence and precarity in the platform economy. *Theory Soc.* 49:833–861.

Schwellnus C, Geva A, Pak M, Veiel R (2019) Gig economy platforms: Boon or bane? Working paper, OECD Economics Department No. 1550, OECD Publishing, Paris.

Silva BC, Moreira AC (2022) Entrepreneurship and the gig economy: A bibliometric analysis. *Management Lett.* 22(2):23–44.

Sundararajan A (2017) *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism* (MIT Press, Cambridge, MA).

Vallas S, Schor JB (2020) What do platforms do? Understanding the gig economy. *Annu. Rev. Sociol.* 46:273–294.

Violante GL (2008) Skill-biased technical change. *New Palgrave Dictionary Econom.* 2:1–6.

Xu Y (2017) Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Anal.* 25(1):57–76.

Zervas G, Proserpio D, Byers JW (2017) The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *J. Marketing Res.* 54(5):687–705.