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

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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 effect heterogeneity 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.

Keywords: Online Gig Platforms, Employment, Skill-Biased Technical Change, Difference-in-Differences, Generalized Synthetic Control

Accepted for Publication in
Information Systems Research

August 2024

1. Introduction

Online gig platforms have, in the recent decade, facilitated the shift of service employment from permanent employment to on-demand gig work (e.g., 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). While 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,

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

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 (e.g., 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 §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.

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 Occupational Information Network (O*NET) Occupational Database.

[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'), while manual-intensive occupations (e.g., cleaners) tend to be at the bottom of the distribution (thereby 'low-skilled').

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 has gradually expanded and operated in more than 40 cities by 2018. We collected the expansion history of TaskRabbit in the United States (U.S.) from 2008 to 2018 and consolidated a unique longitudinal dataset of local employment in housekeeping occupations across the U.S. This dataset aggregates data from the Census Bureau, O*NET database, and American Community Survey, covering occupational information at the MSA (Metropolitan Statistical Area) level for consecutive years between 2005-2018. 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 to 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 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 pre-treatment 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 upon the literature on online gig platforms and labor economics (e.g., Berger et al. 2018, Li et al. 2021), we hypothesize three plausible labor movements: (i) the "*Unemployment Effect*," i.e., online gig platforms replace incumbent (middle-skilled) workers, raising unemployment; (ii) the "*Relocation Effect*", i.e., online gig platforms relocate incumbent middle-skilled workers to similar occupations; and (iii) the "*Self-employment Effect*," i.e., 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 (e.g., 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

[7] Due to 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.

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 (e.g., 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 IS and economics literature has mainly focused on computerization in the labor market (e.g., 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 (e.g., Cramer and Krueger 2016, Schor 2017, Zervas et al. 2017). While 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) while 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 under-explored.

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.

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.

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 §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 Appendix A). The staggered expansion allows us to estimate changes in local employment before and after the platform entry, compared to 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, while 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 to traditional housekeeping businesses in facilitating key functions, such as matching and supervision processes (e.g., 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 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 (e.g., 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 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.

[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.

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. While 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 (e.g., 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 (e.g., Krusell et al. 2000, Acemoglu 2002). Accordingly, the literature documents a shift in labor supply, favoring non-routine 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., 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, while 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 (e.g., 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 (H1a) 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 (e.g., 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 (e.g., 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 (H1b) 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 (H1a and H1b) 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 H1a 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 (e.g., 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 to low-skilled workers. Accordingly, we hypothesize:

Hypothesis 2a: *The proposed negative effects of TaskRabbit entry on (i) the number and (ii) wages of incumbent housekeeping workers (H1a) are stronger for middle-skilled than for low-skilled workers.*

In contrast, if gig platforms positively boost the employment of incumbent workers (i.e., H1b 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, since 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, while 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:

Hypothesis 2b: *The proposed positive effects of TaskRabbit entry on (i) the number and (ii) wages of incumbent housekeeping workers (H1b) 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 (H1a) outweigh the positive effect (H1b), 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*," i.e., incumbent workers lose their jobs and thus become unemployment, ii) the "*Relocation Effect,*" i.e., incumbent workers move to skill-related other occupations, and (iii) the "*Self-employment Effect*," i.e., incumbent workers become self-employed in a similar (housekeeping) occupation.

"The 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. Post 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 (H3a):

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

"The 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 non-housekeeping) occupations, such as those that require similar levels of management and communication skills (Tables C1 and C2 in 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 (H3b):

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.*

"The 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 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

[9] https://support.taskrabbit.com/hc/en-us/articles/204411070-What-s-Required-to-Become-a-Tasker
[10] 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.

typically performed by low-skilled workers, primarily labor-intensive manual tasks, coupled with insufficient managerial and technological skills (see 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 (H3c):

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 and Variable Construction

To empirically test our hypotheses, we consolidated a unique longitudinal dataset 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 (e.g., Ruggles et al. 2019). This micro-level dataset covers 1% of the U.S. population each year and includes anonymous individual-level information on employment status, occupation, wage, and location. This dataset has widely been used in labor economics (e.g., Kerr and Lincoln 2010) and IS literature (e.g., 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 U.S. from the TaskRabbit official website and news articles[13] (See details in Tables A1 and A2 in 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 dataset provides annual subnational economic data by industry and MSA, and it has widely been used in extant IS research (e.g., Kim and Hann 2019). Details of the above data sources are presented in Table A3.

[12] IPUMS covers three types of workers: (i) work-for-wages, (ii) the self-employed, and (iii) the unemployed.
[13] https://www.taskrabbit.com/locations.

We merged and aggregated these data into an MSA-occupation-year level panel dataset containing 24,360 observations covering 267 MSAs[14] and six housekeeping occupations[15] that were consistently identified in the 14-year panel period from 2005-2018.[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); (ii) middle-skilled workers (e.g., first-line managers).

4.2. Variable Definitions

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 dataset. 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.

[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 1 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 since they do not engage in housekeeping-related tasks and are not classified under housekeeping occupations, they are not considered in our analysis.

Independent Variables. Our main independent variable is a dichotomous indicator, $TaskRabbit_{it}$, which equals one if TaskRabbit has operated in MSA_i in $year_t$; 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; otherwise, zero.

Table 3. Key Variables, Definitions, and Descriptive Statistics

Variable (1)	Definition (2)	Mean (3)	S.D. (4)	Min (5)	Max (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.

Location-Specific Time-Varying Covariates. Following existing studies on local employment and online gig platforms (e.g., 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 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 (H1 and H2)

We employed a staggered Difference-in-Differences (DiD) framework with two-way fixed effects to estimate the impact of TaskRabbit entry on local incumbent housekeeping employment (H1), following several IS studies on the impact of online gig platforms (e.g., Burtch et al. 2018, Brynjolfsson et al. 2019). In our setting, DiD estimation compares 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:

$$ln(Y_{ijt}) = \alpha_i + \gamma_j + \theta_t + \beta_1 TaskRabbit_{it} + X_{it}'\beta_2 + \lambda_i t + \delta_i t^2 + \varepsilon_{ijt}, \qquad \text{(Eq. 1)}$$

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

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

To empirically examine the differential effects of TaskRabbit entry on housekeeping workers with distinct skill levels (H2), we included an interaction term between the TaskRabbit entry and Manager occupations (i.e., middle-skilled workers), as in Equation 2.

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

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

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual 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 FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.900	0.900	0.300	0.300

Notes: Robust standard errors (clustered at both MSA and year level) in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

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

[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 in Appendix D).

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 H1a (i) but not H1a (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, while the combination ($\beta_3 + \beta_4$) of $TaskRabbit$ and the interaction term $TaskRabbit \times Manager$ (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 supply of middle-skilled workers is negative and significant, supporting H2a (i). Yet, no evidence suggests that TaskRabbit entry affects the wages of incumbent workers across skill levels (Columns 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 H2a, 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

[24] This number is calculate based on the assumption of a constant treatment effect. More details are provided in 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 Appendix D). Other observed effects remain consistent. These results bolster the notion of a diminished demand for incumbent middle-skilled workers.

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, while 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 (H3)

We explore labor redistribution mechanisms of gig platforms entry, which may help explain the observed main effects. We collected data from the Annual Social and Economic Supplement (ASEC) of the U.S. Current Population Survey (CPS).[27] This data is 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.

H3a-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.

$$Y_{jtf} = \alpha_i + \theta_t + \beta_1 TaskRabbit_{ift} + X_{it}{}'\beta_2 + \lambda_i t + \delta_i t^2 + \varepsilon_{ijtf}, \quad \text{(Eq. 3)}$$

[27] 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).

where Y_{itf} denotes the employment status for the individual f, 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 Eq. 1 and Eq. 2, we include a vector of MSA-year level time-varying covariates (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% = $100 \times (e^{-0.029} - 1)$%, p < 0.05), while Column 2 shows no significant evidence of them moving to other skill-related (but non-housekeeping) occupations. These imply that the "Unemployment Effect" (H3a) and the "Relocation Effect" (H3b) 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., 7.1% = $100 \times (e^{0.069} - 1)$%, p < 0.05), supporting the "Self-employment Effect" (H3c) 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.

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)		
Current employment status:	(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 FE	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 (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

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 Appendix C). To gain a more nuanced understanding of the "Self-employment Effect" (H3c), 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, while self-employed unincorporated workers are more like freelancers or independent contractors who work on their own (Rubinstein and Levine 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) tend to start their own housekeeping startups as entrepreneurs after TaskRabbit entry, rather than working as freelancers or independent workers.

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)	
Current employment status:	(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 FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
# 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

Next, we take another approach to validate the "*Self-Employment Effect*" (H3c) by estimating the changes in the distribution of local housekeeping businesses after TaskRabbit entry. We collected and compiled a longitudinal dataset on the number, sizes, locations, and industries of establishments from U.S. County Business Pattern (See Appendix C) and replicated the baseline DiD model (Eq. 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 5-6, 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.

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

	Dependent Variables: *ln* (# establishment of different employment sizes)								
	Total	1-4	5-9	10-19	20-49	50-99	100-249	250-499	500-999
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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
MSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# 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 1 to 4 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.

In addition to the labor movements hypothesized and tested above, we examined a set of alternative labor movement possibilities (Figure C1, 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 (H3c) 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 to workers in large firms (Table E1, Appendix E), supporting our hypothesis. Additional analysis shows that TaskRabbit's entry significantly reduces working hours for middle-skilled workers (Table E2, Appendix E), further corroborating its role in improving operational efficiency and reducing reliance on these workers.

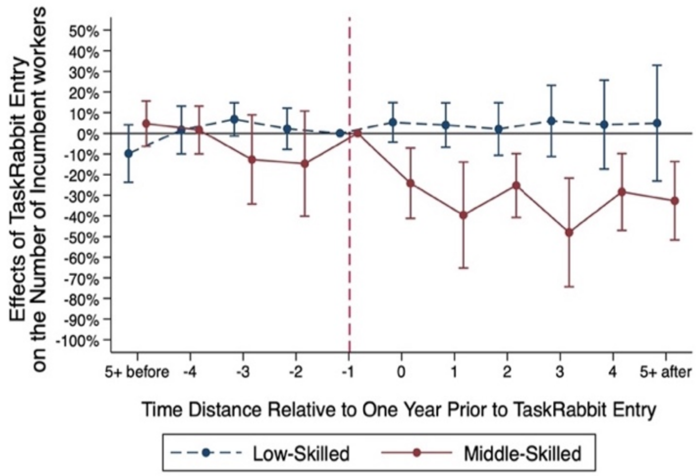
4.5. Robustness Checks

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 pre-treatment trends between TaskRabbit-treated and untreated locations. Following the labor economics and IS literature (e.g., 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 below (also in Table D1, 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.

Figure 1. DiD Estimated Effects of Leads and Lags of TaskRabbit Entry, Over Time



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

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 (e.g., 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, 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 (Eq. 1) 1,000 times. We plotted the distribution of the coefficients of $TaskRabbit_{it} \times Managers_j$ (Figure D1, 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-D4, 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, 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, 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, Appendix D). In each of the above cases, results remained consistent with our baseline DiD estimates.

4.5.3. Enhanced Identification Strategies

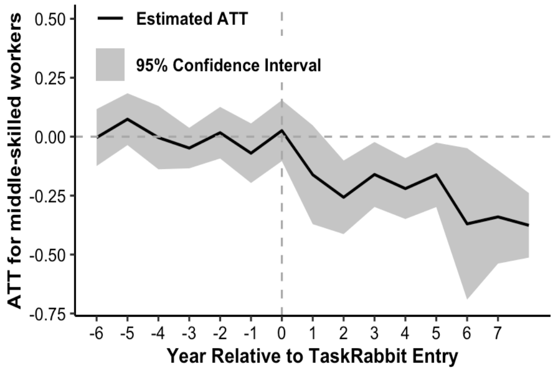
While our results have been consistent thus far, the standard DiD model may face limitations, such as the staggered entry setting and imperfect counterfactuals. To address these concerns, we enhanced our identification strategy with two approaches: heterogeneity-robust DiD and generalized synthetic control.

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).

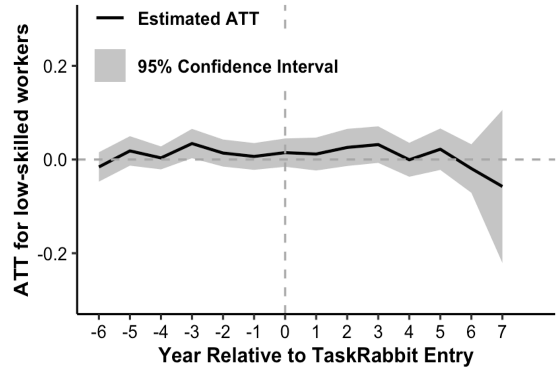
Following the econometric remedies provided by these studies, we first performed Bacon decompositions to decompose our treatment effect into groups based on different controls (i.e., never treated, earlier adopters, and late adopters). Then, we used Callaway and Sant'Anna (2021) estimator to address 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 in 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).

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 pre-treatment periods, which naturally satisfies the parallel trend assumption. Accordingly, the trends of control and treated groups should be very close in the pre-treatment periods, and the differences in employment during the post-treatment 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, 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.

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



(a) Middle-skilled workers



(b) Low-skilled workers

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-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
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

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, 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, Appendix D). Furthermore, although Thumbtack matches 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, 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, 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 (e.g., 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 U.S., 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 (e.g., 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 (e.g., 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 towards highly skilled workers by increasing their relative productivity while substituting low-skilled workers. Although 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 ever-lasting 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 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. While 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. Still, 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 non-randomness 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, 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. While 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 (e.g., Burtch et al. 2018).

Third, while 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, though some subsamples show a negative wage effect on middle-skilled workers (Tables D4 and D18, 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. Due to 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. Finally, our findings are specific to new businesses in the housekeeping industry and may not apply to other industries (e.g., new technology).

6. Concluding Remarks

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.

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SKILL-BIASED TECHNICAL CHANGE, AGAIN?

ONLINE GIG PLATFORMS AND LOCAL EMPLOYMENT

Online Supplementary Appendices

Appendix A. TaskRabbit Entry Information and Main Data Sources

Table A1. TaskRabbit Entry Times and Locations

City	State	Year	City	State	Year
Boston	MA	2008	Detroit	MI	2017
San Francisco	CA	2010	Durham	NC	2017
Chicago	IL	2011	Indianapolis	IN	2017
LA and Orange County	CA	2011	Kansas City	MO	2017
New York	NY	2011	Las Vegas	NE	2017
Portland	OR	2012	Louisville	KY	2017
Seattle	WA	2012	Milwaukee	WI	2017
Austin	TX	2012	Minneapolis	MN	2017
San Antonio	TX	2012	Nashville	TN	2017
Atlanta	GA	2013	Oklahoma City	OK	2017
Dallas	TX	2013	Orlando	FL	2017
Denver	CO	2013	Pittsburgh	PA	2017
Houston	TX	2013	Raleigh	NC	2017
Miami	FL	2013	Sacramento	CA	2017
Philadelphia	PA	2013	Salt Lake City	UT	2017
Phoenix	AZ	2013	St. Louis	MO	2017
San Diego	CA	2013	Tampa	FL	2017
Washington	DC	2013	Oxnard	CA	2017
Ann Arbor	MI	2017	Baltimore	MD	2017
Charlotte	NC	2017	Jacksonville	FL	2018
Cincinnati	OH	2017	Memphis	TN	2018
Cleveland	OH	2017	New Haven	CT	2018
Columbus	OH	2017	St. Paul	MN	2018
Columbus	GA	2017	St. Petersburg	FL	2018

Table A2. TaskRabbit Entry by Year

Year	Entered Areas	Number of Areas
2008	Boston	1
2010	San Francisco	1
2011	Chicago, Orange County, New York,	3
2012	Austin, San Antonio, Portland, Seattle	4
2013	Atlanta, Dallas, Denver, Houston, Miami, Philadelphia, Phoenix, San Diego, Washington DC	9
2017	Ann Arbor, Charlotte, Cincinnati, Cleveland, Columbus (OH), Detroit, Durham, Indianapolis, Kansas City, Las Vegas, Louisville, Milwaukee, Minneapolis, Asheville, Oklahoma City, Orlando, Pittsburgh, Raleigh, Sacramento, Salt Lake City, St. Louis, Tampa, Baltimore	23
2018	Jacksonville, Memphis, New Haven, St. Paul, St. Petersburg	5

Table A3. Key Variables, Definitions, and Data Sources

(1) Variable	(2) Definition	(3) Data Source
Dependent Variables		
ln (number of workers)	Log transformed total number of housekeeping workers	Integrated Public Use Microdata Series
ln (average annual wage)	Log transformed average annual wage of housekeeping workers	
Independent Variables		
TaskRabbit	An indicator that MSA is entered by the TaskRabbit	News & Websites
Manager	An indicator of whether an occupation is a first-line supervisor occupation	O*Net Database
Control Variables		
Population	Log transformed total population	American Community Survey
Density	Log transformed density	
Income	Log transformed per capital income	
Education	% Population with a bachelor's degree or higher	
Sex Ratio	Males per 100 females	
Age Ratio	The population not in the labor force divided by that in the labor force (15-64) and multiplied by 100	
GDP	Log transformed gross domestic product (GDP)	U.S. Bureau of Economic Analysis
Platform service demand	Search intensity index of "TaskRabbit" on Google	Google Trends
Empirical Extensions		
Unemployment	An indicator that a worker transit from middle-skilled housekeeping occupations to unemployment	Annual Social and Economic Supplement
Skill-Related Employment	An indicator that a worker transit from middle-skilled housekeeping occupations to related employment	
Self-Employment	An indicator that a worker transit from middle-skilled housekeeping occupations to self-employment	
ln (# Establishments)	Number of housekeeping establishments	County Business Patterns

Appendix B. Housekeeping Occupations and Skills

Table B1. Technology Skills for Middle-skilled Housekeeping Workers

Middle-skilled workers	Technology skills
1	Computerized bed control system software
2	Computerized maintenance management system CMMS
3	Data entry software
4	Email software
7	Facility use software
8	Help desk software
9	Inventory tracking software
10	Microsoft Access
11	Microsoft Excel
12	Microsoft Office
13	Microsoft Outlook
14	Microsoft PowerPoint
15	Microsoft Project
16	Microsoft Word
17	SAP

Data Sources: The above technology skills are based on the O*NET data set in 2018 for the housekeeping occupation 37-1011: First-Line Supervisors of Housekeeping and Janitorial Workers.

Table B2. Technology Skills for Low-skilled Housekeeping Workers

Middle-skilled workers	Technology skills
1	Microsoft Excel
2	Microsoft Office
3	Microsoft Word

Data Sources: The above technology skills are based on the O*NET data set in 2018 for the housekeeping occupation 37-2011: Janitors and Cleaners.

Table B3. Managerial Skills for Middle and Low-skilled Housekeeping Workers (range 1-5)

Managerial Skills	Middle-skilled	Low-skilled
Time Management	3.75	2.12
Management of Financial Resources	2.75	0
Management of Personnel Resources	3.75	1.38
Management of Material Resources	3	0.25

Data Sources: The managerial skills information is based on the O*NET data set in 2018 for housekeeping occupation 37-1011: First-Line Supervisors of Housekeeping and Janitorial Workers and occupation 37-2011: Janitors and Cleaners.

Table B4. Experience and Annual Wage for Middle and Low-skilled Housekeeping Workers

Workers	Related Work Experience	Mean Wages
Middle-skilled	Majority requires 2-4 years' experience	20.75 hourly
Low-skilled	Majority requires 6 month–1 year experience	13.92 hourly

Data Sources: The experience information is based on the O*NET data set in 2018 for housekeeping occupation 37-1011: First-Line Supervisors of Housekeeping and Janitorial Workers and occupation 37-2011: Janitors and Cleaners. The wages information is acquired through Bureau of Labor Statistics occupational employment and wage statistics.

Appendix C. Underlying Mechanisms

C-1. Related Occupations

Table C1. Most Related Occupations (Right Columns) to Middle-Skilled Housekeeping Workers

O*NET-SOC Code	Title	Related O*NET-SOC Code	Related Title
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	43-1011	First-Line Supervisors of Office and Administrative Support Workers
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	51-1011	First-Line Supervisors of Production and Operating Workers
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	53-1042	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	53-1044	First-Line Supervisors of Passenger Attendants
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	47-1011	First-Line Supervisors of Construction Trades and Extraction Workers
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	45-1011	First-Line Supervisors of Farming, Fishing, and Forestry Workers
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	39-1014	First-Line Supervisors of Entertainment and Recreation Workers, Except Gambling Services

Table C2. Most Related Occupations (Right Columns) to Low-Skilled Housekeeping Workers

O*NET-SOC Code	Title	Related O*NET-SOC Code	Related Title
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	53-7061	Cleaners of Vehicles and Equipment
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	51-6011	Laundry and Dry-Cleaning Workers
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	35-9021	Dishwashers
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
37-2012	Maids and Housekeeping Cleaners	51-6011	Laundry and Dry-Cleaning Workers
37-2012	Maids and Housekeeping Cleaners	39-3093	Locker Room, Coatroom, and Dressing Room Attendants
37-2012	Maids and Housekeeping Cleaners	35-9021	Dishwashers
37-2012	Maids and Housekeeping Cleaners	35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers
37-2021	Pest Control Workers	37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-2021	Pest Control Workers	47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
37-3011	Landscaping and Groundskeeping Workers	37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-3011	Landscaping and Groundskeeping Workers	45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse
37-3011	Landscaping and Groundskeeping Workers	37-3013	Tree Trimmers and Pruners

C-2. Additional Tests for Proposed Underlying Mechanism

1. Individual-worker Level Analysis

We further explored other possible labor movements after TaskRabbit entry. Figure C1 shows a summary of all possibilities. Besides the labor movement (H3a-3c) we hypothesized and tested in the main study, we explored four additional movements: (i) the movement between middle-skilled and low-skilled incumbent workers within housekeeping occupations, (ii) the bidirectional movement between housekeeping occupations and skill-related (non-housekeeping) occupations, and (iii) the bidirectional movement between housekeeping occupations and TaskRabbit-related (non-housekeeping) occupations, and (iv) the transition from low-skilled cumbent workers to self-employment.

First, workers may move between middle-skilled and low-skilled housekeeping occupations after the gig platform entry. According to Rauf (2014), many middle-skilled managers were previously cleaners and janitors and later promoted after several years of work experience. Hence, these middle-skilled workers possess the essential skills to perform the tasks of low-skilled workers. Should TaskRabbit substitutes incumbent middle-skilled workers by automating their managerial tasks, these workers would move back to low-skilled housekeeping occupations. If so, we would expect an increase in the transitions from middle-skilled housekeeping occupations to low-skilled ones after TaskRabbit entry. Meanwhile, TaskRabbit entry may reduce the transitions from low-skilled occupations to middle-skilled ones, given the decreased demand for housekeeping managers in traditional businesses. We empirically tested these competing explanations. However, no evidence supports such labor movements after the TaskRabbit entry (Table C3). This finding precludes the alternative explanations and lends more credence to the proposed "Self-Employment" movement as the major labor redistribution effect of online gig platforms.

Second, we further explored the labor moment between housekeeping occupations and skill-related other occupations that share similar skills with housekeeping occupations. Results are presented in Table C4. As seen, no evidence suggests such a movement.

Third, as a robustness check, we examined the labor moment between housekeeping occupations and other TaskRabbit-related but non-housekeeping occupations. As TaskRabbit offers other types of services (i.e., moving), these services may influence the effect we observed in regard to housekeeping workers (e.g., other workers enter the housekeeping industry, or housekeeping workers enter the moving industry). Table C5 presents the results, indicating any statistically significant movement, which helps to alleviate the concerns that other services covered by TaskRabbit bias our baseline estimates.

Finally, our empirical analysis so far has indicated a null effect of labor movement for low-skilled workers, but it is possible that the null effect results from two countervailing effects cancelling out each other: A) online gig platforms attract more low-skilled workers into the industry to work for housekeeping firms, and B) they attract low-skilled workers to leave their work-for-wage status and become self-employed. Empirically, we employed individual-level data for low-skilled workers to explore whether TaskRabbit promotes them to pursue self-employment opportunities. The results, shown Table C6, indicate no statistically significant movement from low-skilled wage-based employment to either type of self-employment (i.e., incorporated and unincorporated), failing to support effect (B). Given this rationale, we reasonably believe that the cancel-out effect is less likely. Our additional findings suggest that low-skilled workers may not transition because online gig platforms cannot directly replace low-skilled workers, and these workers have little incentive to move to self-employment.

Figure C1. Labor Movement Framework

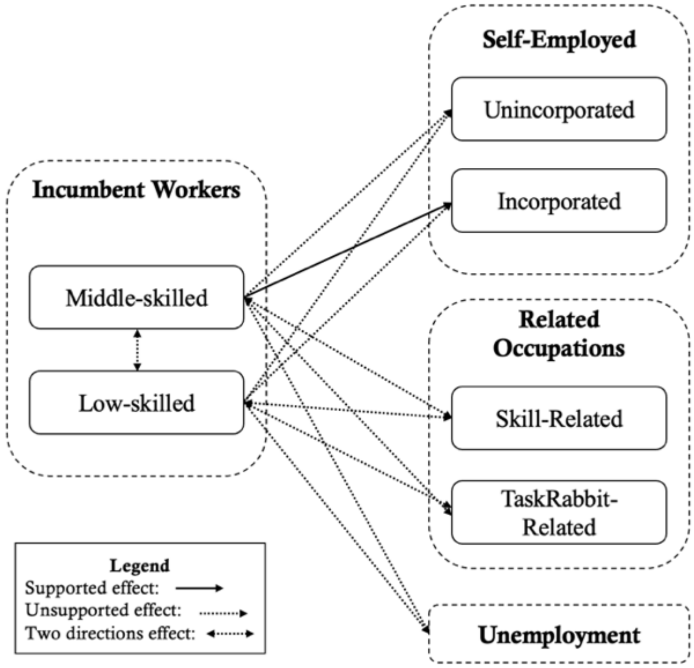


Table C3. TaskRabbit Effect on the Probability of Individual Transition between the Middle- and Low-skilled Housekeeping Occupations

	Dependent Variables:	
Linear Probability Model	whether a middle-skilled housekeeping worker becomes a low-skilled worker (0/1)	whether a low-skilled housekeeping worker becomes a middle-skilled worker (0/1)
TaskRabbit	-0.003	-0.000
	(0.004)	(0.000)
Time-varying Covariates	Yes	Yes
MSA and Year FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
# Observations	3,221,667	48,071,753
Adjusted R^2	0.008	0.021

Notes: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table C4. TaskRabbit Effect on the Probability of Individual Transition between the Housekeeping Workers and *Skill-related* (Non-Housekeeping) Occupations

Linear Probability Model	*Dependent Variables*: whether a housekeeping worker becomes a worker in skill-related non-housekeeping occupations (0/1)	whether a worker in skill-related non-housekeeping occupations becomes a housekeeping worker (0/1)
TaskRabbit	-0.001	0.002
	(0.002)	(0.002)
Time-varying Covariates	Yes	Yes
MSA and Year FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
# Observations	65,751,515	65,176,302
Adjusted R^2	0.008	0.010

Notes: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table C5. TaskRabbit Effect on the Probability of Individual Transition between the Housekeeping Workers and *Other* Occupations that TaskRabbit Offers Similar Services

Linear Probability Model	*Dependent Variables*: whether a housekeeping worker becomes employed in other occupations TaskRabbit offered related services (0/1)	whether a worker in other occupations TaskRabbit offered related services becomes a housekeeping worker (0/1)
TaskRabbit	-0.007	-0.006
	(0.007)	(0.005)
Time-varying Covariates	Yes	Yes
MSA and Year FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
# Observations	65,751,515	72,607,867
Adjusted R^2	0.007	0.008

Notes: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table C6. TaskRabbit Effects on the Probability of Individual Transition between Low-skilled Housekeeping Workers and Self-Employment

	Dependent Variables: whether an incumbent housekeeping worker (middle-skilled or low-skilled) changed status from work-for-wages employment to the following (1/0)		
Linear Probability Model	(1) Self-employed *Total*	(1) Self-employed *Incorporated*	(2) Self-employed *Unincorporated*
TaskRabbit	-0.001	-0.002	0.001
	(0.002)	(0.002)	(0.000)
Time-varying Covariates	Yes	Yes	Yes
MSA and Year FE	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes
Observations	48,387,245	48,165,444	48,275,087
Adjusted R-squared	0.411	0.090	0.574

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

2. Aggregate MSA-Year Level Analyses

To ensure the robustness of our findings on the labor redistribution effects (H3a-3c) for middle-skilled workers, we explored the effects of TaskRabbit entry on the overall number of workers in unemployment, housekeeping-related occupations, and self-employment in the housekeeping middle-skilled occupations using aggregate MSA-year level data. Like our main analysis, we collected detailed employment data from IPUMS dataset from the U.S. Census Bureau.

Table C7 shows the results. While TaskRabbit entry does not significantly affect the number of workers in unemployment and skill-related occupations (Columns 1 and 2), it significantly increases the number of self-employed workers in the housekeeping middle-skilled occupations by 6.3% ($p < 0.05$, Column 4). Furthermore, we do not observe significant effects of TaskRabbit on the average annual wage of workers in skill-related occupations in other industries and self-employed workers in the housekeeping industry. The results from the aggregate level analysis are highly consistent with those using the individual worker data, further corroborating the hypothesized self-employment effect (H3c).

Table C7. DiD Estimated Effect of TaskRabbit on Unemployment and Self-employment

	Dependent Variables: ln (number of workers) belongs to the following categories				
	Unemployed (H3a)	Skill-related Occupations (H3b)		Self-Employed (H3c)	
	ln (# workers)	*ln* (# workers)	*ln* (avg. wage)	*ln* (# workers)	*ln* (avg. wage)
	(1)	(2)	(3)	(4)	(5)
TaskRabbit	-0.018	0.010	-0.000	0.063**	-0.030
	(0.084)	(0.006)	(0.006)	(0.023)	(0.021)
Time-varying Covariates	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes	Yes
# Observations	2,370	3,675	3,675	3,371	3,675
Adjusted R^2	0.805	0.998	0.872	0.880	0.338

Notes: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

C-3. Summary Statistics of County Business Patterns

Table C8 below shows the summary statistics of variables from County Business Patterns (CBP) that we used in the analyses in regard to Table 7.

County Business Patterns have been widely used in prior studies to examine or control the number of local establishments by industry. For instance, Greenwood and Gopal (2015) explored the impact of media coverage on entrepreneurial activities, and they used the CBP data to control the number of local IT firms and IT workers. Kim and Hann (2019) examined the difficulty of obtaining bank loans and the crowdfunding use by entrepreneurs, and they use the CBP data to control number of small establishments.

In our study, we followed the literature and used CBP data to examine the changes in the number of newly-established housekeeping businesses (with different sizes) after the TaskRabbit entry to better understand the underlying labor movement mechanisms.

Table C8. Descriptive Statistics of Variables We Used from County Business Patterns

Variables	(1) Description	(2) mean	(3) std. dev.	(4) min	(5) max
Emp	Total mid-March employees	646,693	2.504e+06	4,776	5.102e+07
Est	Total number of establishments	46,004	169,190	595	3.488e+06
n1_4	Number of establishments with employment size class:1-4 employees	21,290	91,514	0	2.116e+06
n5_9	Number of establishments with employment size class:5-9 employees	8,506	28,378	84	563,073
n10_19	Number of establishments with employment size class:10-19 employees	5,848	19,375	52	368,671
n20_49	Number of establishments with employment size class:20-49 employees	4,058	13,797	24	259,263
n50_99	Number of establishments with employment size class:50-99 employees	1,369	4,828	0	85,555
n100_249	Number of establishments with employment size class:100-249 employees	772.2	2,838	0	50,620
n250_499	Number of establishments with employment size class:250-499 employees	190.3	729.8	0	14,489
n500_999	Number of establishments with employment size class:500-999 employees	67.90	263.7	0	5,274
n1000	Number of establishments: employment size class:1,000 Or more employees	39.23	167.9	0	3,528

Appendix D. Robustness Checks

D-1. Validity of the Baseline DiD Estimator

1. Examining the Parallel Trend Assumption

The critical assumption of the DiD estimates lies in no difference in the pre-treatment employment trends between treated and untreated MSAs (i.e., parallel trend assumption). A violation of this could be caused by nonrandom selection of the platform entry into certain areas. To check its possibility, following the prior labor economics and IS literature (e.g., Autor 2003, Chan and Ghose 2014), we modify Equation 1 to include a set of dummy variables to indicate the relative temporal distance (d or k) between a given year (t) and the year (t_0) when TaskRabbit entered a given MSA. The model is outlined below:

$$\begin{aligned} ln(Y)_{ijt} = &\sum_d \tau_d PreTaskRabbitEntry_{it-d}(d) + \sum_k w_k PostTaskRabbitEntry_{it+k}(k) \\ &+ \textstyle\sum_d \tau'_{d_d} PreTaskRabbitEntry_{it-d}(d) * Managers_j \\ &+ \textstyle\sum_k w'_{k_k} PostTaskRabbitEntry_{it+k}(k) * Managers_j \\ &+ X'_{it}\beta_6 + \alpha_i + \gamma_j + \theta_t + \lambda_i t + \delta_i t^2 + \varepsilon_{it}, \qquad \text{(Eq. 3)} \end{aligned}$$

where $PreTaskRabbitEntry_{it-d}$ is an indicator that equals one if year t is d years (d > 1) prior to the TaskRabbit entry MSA i. $PostTaskRabbitEntry_{it+k}$ is an indicator that equals one if year t is k years (k ≥ 0) post the entry. Specifically, τ_d allows us to test if there is any difference in pre-treatment trends between treated and untreated MSAs. The interaction of these two indicators and $Managers_j$ explore the pre- and post-treatment trends for middle-skilled workers. Following extant studies (Autor 2003, Brynjolfsson et al. 2019), one year before the TaskRabbit entry (d = 1) is omitted as the baseline.

Results are in Table D1 (next page) and visualized in Figure 1 (in the main manuscript). As can be seen, there are no statistically significant differences in the trends of both the number and wage of workers between treated and untreated MSAs in the pre-treatment periods, failing to reject the parallel trends assumption of the DiD estimates. Notably, we observe a statistically significant and persistent downward trend in the number of middle-skilled workers (e.g., managers) after the TaskRabbit entry, while the effect on low-skilled workers (e.g., cleaners) is not significant. Finally, we find the effects on the average annual wage of housekeeping workers are insignificant before and after TaskRabbit entry. These results support the validity of the baseline DiD estimates.

Table D1. DiD Estimated Effects of Leads and Lags of TaskRabbit Entry, Over Time

	Dependent Variables:	
	ln (Number of Workers)	*ln* (Average Annual Wage)
	(1)	(2)
TaskRabbit Entry 5 or more years before	-0.098 (0.071)	0.105 (0.062)
TaskRabbit Entry 5 or more years before * Manager	0.047 (0.056)	0.030 (0.040)
TaskRabbit Entry 4 years before	0.016 (0.059)	0.064 (0.039)
TaskRabbit Entry 4 years before * Manager	-0.135 (0.078)	0.009 (0.043)
TaskRabbit Entry 3 years before	0.068 (0.041)	0.060+ (0.032)
TaskRabbit Entry 3 years before * Manager	-0.127 (0.110)	0.026 (0.043)
TaskRabbit Entry 2 years before	0.022 (0.051)	0.040 (0.029)
TaskRabbit Entry 2 years before * Manager	-0.147 (0.130)	0.028 (0.084)
TaskRabbit Entry 1 year before	omitted baseline	
TaskRabbit Entry 1 year before * Manager	omitted baseline	
TaskRabbit Entry	0.053 (0.049)	0.018 (0.047)
TaskRabbit Entry * Manager	-0.242* (0.087)	0.019 (0.087)
TaskRabbit Entry 1 year after	0.040 (0.055)	-0.077 (0.062)
TaskRabbit Entry 1 year after * Manager	-0.396** (0.131)	0.083 (0.047)
TaskRabbit Entry 2 year after	0.021 (0.065)	-0.104+ (0.056)
TaskRabbit Entry 2 year after * Manager	-0.253** (0.079)	0.010 (0.058)
TaskRabbit Entry 3 year after	0.060 (0.088)	-0.110 (0.080)
TaskRabbit Entry 3 year after * Manager	-0.480** (0.134)	0.006 (0.055)
TaskRabbit Entry 4 year after	0.042 (0.110)	-0.150 (0.099)
TaskRabbit Entry 4 year after * Manager	-0.284* (0.095)	0.018 (0.057)
TaskRabbit Entry 5 or more years after	0.049 (0.143)	-0.167 (0.102)
TaskRabbit Entry 5 or more years after * Manager	-0.327** (0.097)	-0.057 (0.061)
Time-varying Covariates	Yes	Yes
Year FE	Yes	Yes
MSA FE	Yes	Yes
Occupation FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
# Observations	18,096	18,096
Adjusted R-squared	0.898	0.300

Notes: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

2. Reverse Causality—Discrete Time Hazard Model

Next, we address a potential concern that the TaskRabbit entry may be determined by past employment and wage status in the housekeeping industry. This is akin to the concern of reverse causality. In this case, the TaskRabbit entry cannot be treated as-if randomly assigned, conditional on observable covariates (i.e., geographical areas controls and year and MSA fixed effects), where the estimations of TaskRabbit effects could be biased. To address this potential concern, we used the discrete-time hazard model (Jenkins 1995) to predict TaskRabbit entry using past employment levels in one year, two years, and three years prior to the TaskRabbit entry and the time-varying covariates of the MSA in the entry year. This model enables us to directly examine if the past employment status of an MSA determines the introduction of TaskRabbit.

Results are in Table D2. As seen, the number and average wage of workers in the past years do not statistically significantly predict TaskRabbit entry, precluding the concern of reverse causality.

Table D2. Discrete Time Hazard Model

	Dependent Variable: TaskRabbit Entry at year t *Independent Variables:* Past trends in the following					
	ln (Number of Workers)			*ln* (Average Annual Wage)		
	(1) Total	(2) Manager	(3) Cleaner	(1) Total	(2) Manager	(3) Cleaner
Number (t-1)	-0.000	0.006	-0.002			
	(0.003)	(0.004)	(0.003)			
Number (t-2)	-0.005	0.003	-0.005			
	(0.005)	(0.005)	(0.006)			
Number (t-3)	0.008	0.002	0.007			
	(0.005)	(0.002)	(0.004)			
Wage (t-1)				0.004	-0.005	0.007
				(0.005)	(0.005)	(0.008)
Wage (t-2)				0.005	-0.003	0.008
				(0.005)	(0.005)	(0.006)
Wage (t-3)				0.002	0.007	0.003
				(0.005)	(0.006)	(0.005)
Time-varying Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Location Specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	2,743	1,945	2,743	2,743	1,931	2,743
Adjusted R-squared	0.121	0.120	0.121	0.121	0.119	0.121

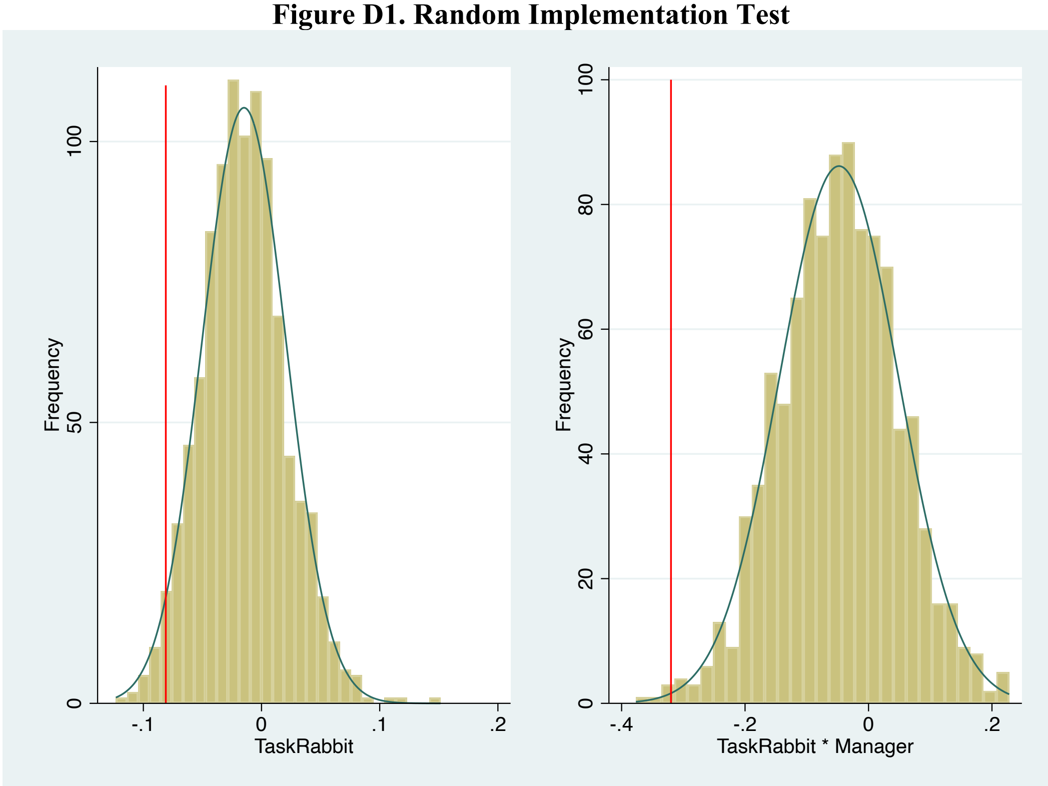
Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

3. A Permutation Test Using Placebo Treatments

We further consider the possibility of false significance due to general downward trends in the dependent variable or spurious effects (Bertrand et al. 2004). Following Greenwood and Agarwal (2016) and Burtch et al. (2018), we conducted a permutation test by randomly shuffling the placebo treatment variables (i.e., *TaskRabbit*), and we then ran the DiD model in Eq. 1 and Eq. 2 using the shuffled placebo treatments and store the estimates. This procedure is replicated 1,000 times with different sets of random treatments.

Figure D1 shows the distribution of the pseudo effects, which are centered around zero, and the t-test fails to reject the null hypothesis that the average estimated effect based on random treatments is statistically different from zero. In addition, comparing the distribution of the pseudo effects of random official TaskRabbit entry, we observe that the real DiD estimate of both the actual TaskRabbit entry effect and the interaction effects is at the left tail of the distribution (higher than the 95% percentile). These results show that our baseline estimates are not due to spurious statistical significance.

Figure D1. Random Implementation Test



D-2. Sample Selection

1. Coarsened Exact Matching

We address a potential selection issue; that is, MSAs having yet to be chosen by TaskRabbit might not be an ideal counterfactual to the treated MSAs. To remedy this, we use Coarsened Exact Matching (CEM) to improve the estimation by reducing the imbalance in covariates between treated and control groups (Blackwell et al. 2009, Iacus et al. 2012). CEM has widely been used to address selection bias in IS studies (e.g., Bapna et al. 2016). Specifically, we matched the treated MSAs and the controlled MSAs using observable characteristics, such as the population, education level, and income before treatment started (i.e., 2008). Table D3 presents examples of matched MSAs.

Results from replicating the main analysis with matched MSAs are in Table D4. A significant negative effect of the TaskRabbit entry remains, alleviating the concerns of the imperfect comparability between treated and untreated MSAs in our baseline DiD estimation.

Table D3. Examples of Matched MSAs

Matched Treated MSAs	Matched Control MSAs
• Cincinnati, OH-KY-IN • Cleveland-Elyria, OH • Detroit-Warren-Dearborn, MI • Jacksonville, FL • Joinville/Jefferson County, IN • Memphis, TN-MS-AR • Nashville-Davidson-Murfreesboro-Franklin, TN • New Haven-Milford, CT • Oklahoma City, OK • Oxnard-Thousand Oaks-Ventura, ca • Pittsburgh, PA	• Allentown-Bethlehem-Easton, PA-NJ • Birmingham-Hoover, AL • Columbia, SC • Harrisburg-Carlisle, PA • Hartford-West Hartford-East Hartford, CT • New Orleans-Metairie, LA • Providence-Warwick, RI-MA • Rochester, NY • San Jose-Sunnyvale-Santa Clara, CA • Santa Maria-Santa Barbara, CA • Virginia Beach-Norfolk-Newport News, VA

Table D4. DiD Estimates Adjusted Using Coarsened Exact Matched MSAs

	Dependent Variables:			
	(1)	(2)	(3)	(4)
	ln (Number of Workers)		*ln* (Average Annual Wage)	
TaskRabbit	-0.062	0.076	0.131	0.183*
	(0.136)	(0.148)	(0.083)	(0.077)
TaskRabbit × Manager		-0.398**		-0.150*
		(0.102)		(0.068)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes
# Observations	2,047	2,047	2,047	2,047
Adjusted R^2	0.861	0.862	0.349	0.349

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

2. Sample Selection—Only Treated MSAs Included

We continue addressing selection issues with a concern that the treated and untreated MSAs may follow different employment trends in the pre-treatment periods, which may violate the parallel trends assumption. To reduce this concern, we only included treated MSAs in our sample to restrict the control group to units that have not yet received but would eventually receive treatments. In this case, the control units are more likely to share unobservable characteristics, thereby alleviating the related endogeneity concern.

We replicated the main analysis on the subsample, and the results are in Table D5. The significant negative effects of TaskRabbit remain, further supporting the baseline DiD estimate.

Table D5. Replication of Main Table (Including Only Treated MSAs)

	Dependent Variables:			
	(1)	(2)	(3)	(4)
	ln (Number of Workers)		*ln* (Average Annual Wage)	
TaskRabbit	-0.083*	0.019	0.020	0.024
	(0.030)	(0.041)	(0.026)	(0.029)
TaskRabbit × Manager		-0.305***		-0.012
		(0.067)		(0.027)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes
# Observations	3,662	3,662	3,662	3,662
Adjusted R^2	0.941	0.943	0.633	0.633

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

3. Sample Selection—Drop MSAs Entered after 2017

It is likely that the effect of TaskRabbit entry might have taken more than one year to fully materialize. As our data ranges from 2005 to 2018, we removed MSAs that TaskRabbit entered after 2017 and reran the analysis. Results are in Table D6 and are consistent with the main results.

Table D6. Replication of Main Table (Excluding MSAs Entered after 2017)

	Dependent Variables:			
	(1)	(2)	(3)	(4)
	ln (Number of Workers)		*ln* (Average Annual Wage)	
TaskRabbit	-0.092***	0.012	-0.014	-0.018
	(0.021)	(0.026)	(0.039)	(0.038)
TaskRabbit × Manager		-0.312***		0.013
		(0.059)		(0.034)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes
# Observations	16,275	16,275	16,275	16,275
Adjusted R^2	0.896	0.897	0.286	0.286

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4. Sample Selection—Top 50 Largest MSAs Included

Online gig platforms are more likely to enter cities with a large population (Berger et al. 2018). Hence, we only included the top 50 largest MSAs and replicated the DiD estimation. Results are in Table D7, where we observe consistent results with the main analysis.

Table D7. Replication of Main Table (Only Including Top 50 Largest MSAs)

	Dependent Variables:			
	(1)	(2)	(3)	(4)
	ln (Number of Workers)		*ln* (Average Annual Wage)	
TaskRabbit	-0.095**	0.002	0.008	0.015
	(0.023)	(0.031)	(0.025)	(0.027)
TaskRabbit × Manager		-0.292***		-0.022
		(0.058)		(0.021)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes
# Observations	4,143	4,143	4,143	4,143
Adjusted R^2	0.939	0.941	0.566	0.566

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

5. Sample Selection—Drop Time Periods after 2017

Finally, in 2017, TaskRabbit was acquired by IKEA, and it then offered additional services, such as furniture assembly and delivery services, which may confound our main results. Thus, the sample before 2017 would be a cleaner sample that contains fewer categories of services,[30] and cleaning is one of the most popular services provided by TaskRabbit. We find consistent results (Table D8).

Table D8. Replication of Main Table (Excluding Data After 2017)

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.078*	0.037	-0.015	-0.018
	(0.026)	(0.030)	(0.037)	(0.038)
TaskRabbit × Manager		-0.342***		0.009
		(0.069)		(0.029)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	15,957	15,957	15,957	15,957
Adjusted R^2	0.900	0.901	0.295	0.295

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

[30] Major categories provided: cleaning, delivery, errands, furniture assembly, help moving, mounting, shopping, and yard work and removal.

D-3. Enhanced Identification Strategy

1. Heterogeneity-Robust DiD Model

Recent studies have suggested that the standard DiD model may lead to a biased estimation when the treatment happens at different time periods by comparing the earlier adopters with the late adopters (Goodman-Bacon 2021, Baker et al. 2022) when there exist dynamic treatment effects. To address this concern, we first used the Bacon Decomposition (Goodman-Bacon 2021) to show the estimates for three groups of DiD pairs in our data. The results and visualization are presented in Figure D2 and Table D9. As seen, the effects of TaskRabbit on the number of housekeeping workers are negative for all three groups, suggesting that main negative effects we observed are not driven by the timing-varying group.

Figure D2. Scatterplot of Bacon Decomposition

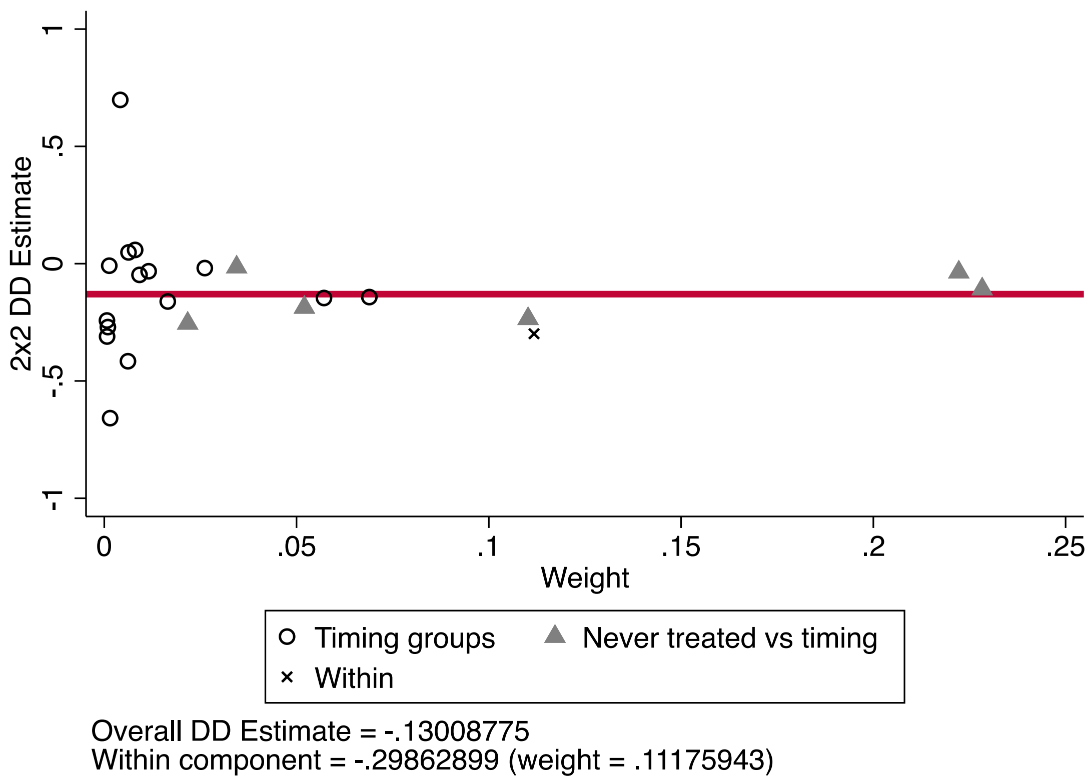


Table D9. Bacon DiD Decomposition

	Beta	Total Weight
Timing groups	-0.1034666	0.21931963
Never treated vs timing	-0.1114551	0.66892094
Within	-0.298629	0.11175943

To provide more accurate estimates, we used the heterogeneity-robust DiD model originally proposed by Callaway and Sant'Anna (2021) to estimate the treatment effect by different cohorts and then aggregated them together based on the sample size. Specifically, we only used the never-treated MSAs as the control group to address the potential dynamic treatment effect. As seen in Table D10, we still observe significant effects for middle-skilled workers while no effect for low-skilled workers.

Table D10. Staggered Entry Model – Callaway and Sant'Anna (2021)

	Middle-Skilled Workers		*Low-Skilled Workers*	
DV:	*ln* (number)	*ln* (wage)	*ln* (number)	*ln* (wage)
TaskRabbit	-0.448***	0.028	-0.008	0.083
	(0.163)	(0.136)	(0.084)	(0.072)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
# Observations	4,951	4,951	12,267	12,267

Note: Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

2. Generalized Synthetic Control

While we used the DiD framework to establish our primary evidence for the effects of TaskRabbit entry, the parallel trend assumption is not directly testable. It is possible that DiD estimates might be biased when unaccounted time-varying confounders influence treated and untreated MSAs differently. To further address this issue, we employ a Generalized Synthetic Control (GSC) approach (Xu 2017), which is the combination of a synthetic control model (Abadie and Gardeazabal 2003, Abadie et al. 2010) 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 pre-treatment periods, which naturally satisfies the parallel trend assumption. Accordingly, the trends of control and treated groups should be very close in the pre-treatment periods, and the differences in employment during the post-treatment 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).

The synthetic control method has recently gained popularity in IS research (Pattabhiramaiah et al. 2019, Krijestorac et al. 2020, Wang et al. 2021) and other social sciences disciplines for causal inference (Guo et al. 2020). We use the GSC method because it features two properties that the traditional synthetic control method lacks: (i) incorporating a two-way fixed effect structure, and (ii) allowing multiple treated units and periods for the estimation. GSC is a good fit to our empirical context, i.e., multiple fixed effects, given the staggered expansion of TaskRabbit into multiple locations at different times (rather than a one-time entry into one location). Notably, the current GSC method has yet to allow analysis at the MSA-year-occupation level (i.e., more than two levels). For GSC analysis, we split our sample by occupation (i.e., middle-skilled and low-skilled) and collapsed the data into MSA-year level (267 MSAs in 14 years).

The estimation results are in Table D11. The effect of TaskRabbit entry on the number of housekeeping managers is negative and statistically significant ($\beta = -0.146$, $p < 0.01$), while effect of TaskRabbit entry on the number of low-skilled workers is not significant ($p = 0.48 > 0.1$), supporting our hypotheses (H2a).

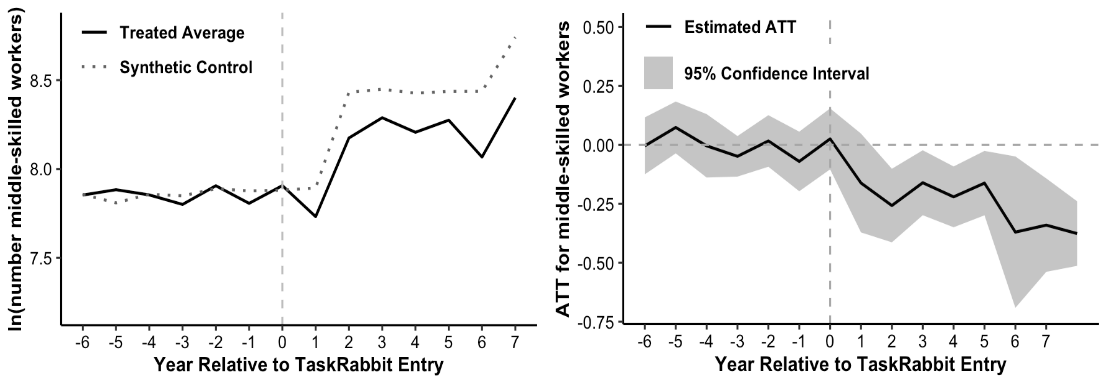
Table D11. Generalized Synthetic Control: TaskRabbit Effects on Local Housekeeping Workers

	Dependent Variables:			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	Middle-skilled	Low-skilled	Middle-skilled	Low-skilled
	(1)	(2)	(3)	(4)
TaskRabbit	-0.146***	0.011	0.050	-0.032
	(0.035)	(0.016)	(0.092)	(0.042)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
# Observations	5,018	12,142	5,018	12,142

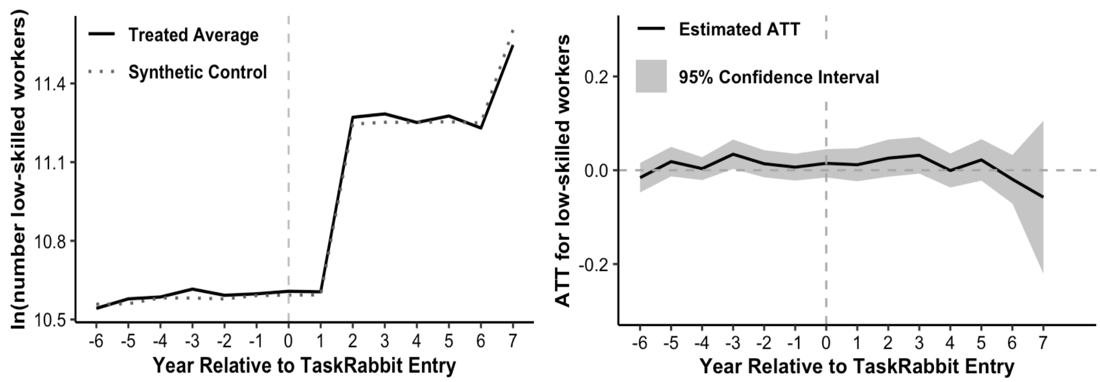
Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Bootstrapped standard errors in parentheses (1000 reps). *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure D3 visualizes the comparison between the treated and synthetic control groups over time. As seen, pre-treatment trends in middle-skilled employment of treated and untreated locations are remarkably close to each other, while middle-skilled employment declines significantly after the TaskRabbit Entry. However, the trends in low-skilled employment remain overlapped before and after the TaskRabbit Entry. Accordingly, the GSC results further support the baseline DiD estimates.

Figure D3. GSC Estimated Effects of TaskRabbit on Housekeeping Employment



(a) Middle-skilled workers



(b) Low-skilled workers

D-4. Impacts of Other Platforms

1. Detailed Survey of Major Competitors of TaskRabbit

We offer a detailed survey of the major competitors of TaskRabbit (Table D12). As seen on Table D12, some gig platforms are much smaller than TaskRabbit (e.g., Tidy, Jiff), and some entered the US market outside of our study period (e.g., Airtasker),[31] and thus they may not be comparable with TaskRabbit. Accordingly, our study focused on two online gig platforms that have a similar staggered expansion history and size as with TaskRabbit—Thumbtack and Handy. It is worth noting that, Thumbtack entered more than 447 cities in the first year in the market and then gradually expanded to a few more cities each year, which leads to the low variations of the treatment.

Table D12. Related Platforms Statistics

Platforms	Revenue	Employees	Year in the U.S.	Staggered Entry	Compared with TaskRabbit
TaskRabbit	244.9M	1,181	2008	Yes	Focus of the study
Thumbtack	300M	1,791	2009	No	Entered the majority of the U.S. cities in 2009.
Handy	216.6M	1,082	2012	Yes	Similar entry history
Craigslist	77.4M	427	2004	Yes	Consumers post ads and does not provide online matching.
Airtasker	57.4M	328	2021	Yes	Enter U.S. after data period.
Dolly	41.8M	155	2015	Yes	Service areas focus on moving services and does not provide cleaning services
Tidy	19.5M	NA	2014	NA	Relatively smaller size, entry date is not available
Jiffy	4.9M	42	2018	Yes	Services just in Boston and Chicago
AllBetter	<5M	25	2016	NA	Much smaller size than TaskRabbit
Maidsapp	<1M	<10	2014	NA	Much smaller size than TaskRabbit

Sources: Data were collected from multiple websites including https://growjo.com/company/ and individual platform websites.

[31] Some competitors like Molly Maids and The Maids enter US long before the existence of gig platforms. These companies use the traditional housekeeping business model match clients instead of the online matching.

2. Accounting for the Effect of Handy

According to our analyses of the competitors of TaskRabbit (Table D12), Handy is one platform that has similar size, service areas, and expansion history as TaskRabbit. Therefore, we acquired the entry data of Handy and empirically tested the role of Handy entry in the supply of incumbent housekeeping workers. The results are presented in Tables D13-D14. We found similar negative effects of the entry of Handy on middle-skilled workers, corroborating the generalizability of our main findings from TaskRabbit.

Table D13. Replication of Main Table Using Handy Entry Data

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
Handy	-0.044	0.064	0.020	0.023
	(0.055)	(0.056)	(0.038)	(0.035)
Handy × Manager		-0.322***		-0.009
		(0.053)		(0.032)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.897	0.898	0.300	0.300

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D14. Replication of Main Table Including Both TaskRabbit and Handy Entry Data

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.068*	0.007	0.012	0.007
	(0.026)	(0.034)	(0.034)	(0.038)
TaskRabbit × Manager		-0.225**		0.014
		(0.073)		(0.045)
Handy	-0.020	0.027	0.016	0.022
	(0.059)	(0.063)	(0.044)	(0.044)
Handy × Manager		-0.141*		-0.020
		(0.057)		(0.051)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.897	0.898	0.300	0.300

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

3. Accounting for the Effect of Thumbtack
In addition, another platform may potentially influence our observed empirical effect is Thumbtack. Even though the platform entered the majority of US cities in one year, the time fixed effects and both linear and quadratic time trends may not adequately capture these variations. To address this concern, we further explored the differences between TaskRabbit and Thumbtack, and we provide empirical evidence below.

First, we note the differences between TaskRabbit and Thumbtack in their matching processes. TaskRabbit allows users to directly select and book a "Tasker" based on hourly rates and reviews, whereas Thumbtack provides multiple quotes from professionals after a job description is posted, allowing for price and profile comparisons, but not completing the matching on the platform. In addition, initially Thumbtack was merely a classified sites and directories like Yelp. It changed its business model around 2011. These could suggest a less direct role in matching compared to TaskRabbit, which may limit the strength of its impact. Furthermore, it is important to note that Thumbtack offers a wider range of services than TaskRabbit, including sectors like wedding photography and tax consultation, which means the impact of housekeeping services is only a small fraction of its overall operations and tasks available.

Empirically, we followed the approach of prior studies and used Google Trends as a proxy to gauge its influence (e.g., Chan et al. 2019, Bacher-Hicks et al. 2022). We included the search intensities for "Thumbtack" across different MSAs in our data periods. The results are presented in Table D15 and show consistent results.

Table D15. Replicating Main Model with Thumbtack Search Intensity

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.113**	0.018	-0.002	-0.010
	(0.033)	(0.038)	(0.000)	(0.000)
TaskRabbit × Manager		-0.387***		0.025
		(0.068)		(0.000)
Thumbtack Search Intensity	-0.092	-0.092	0.022	0.022
	(0.058)	(0.058)	(0.000)	(0.000)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	14,045	14,045	14,045	14,045
Adjusted R^2	0.879	0.880	0.270	0.270

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4. Accounting for the Number of Competitors

Next, we replicated the baseline estimation using the number of platforms entered in MSAs as a proxy for treatment intensity, and we observed similar and consistent patterns with our main findings (Table D16).

Table D16. Replication of Main Table with the Number of Platform Entry

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
Platform Number	-0.048+	0.014	0.014	0.014
	(0.023)	(0.023)	(0.016)	(0.016)
Platform Number × Manager		-0.186***		-0.002
		(0.030)		(0.016)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.897	0.898	0.300	0.300

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

5. Excluding Effects from Gig Platforms that Might Disrupt Other Industries/Occupations
We further addressed the potential confounders of the observed effects from gig platforms in other industries, such as Airbnb. To address this concern, we generated two groups of dependent variables (1) excluded all housekeeping workers who work in the traveler accommodation industry and (2) just focused on workers from the building and dwelling industry (i.e., the main industry that involves housekeeping occupations we focused on empirically).

The results are presented in Tables D17 and D18, and they are largely consistent. Notably, as shown in Table D18, 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 statistically significantly. These results bolster the notion of a diminished demand for middle-skilled workers in traditional housekeeping businesses.

Table D17. Replication of Main Table (Excluding Workers in Traveler Accommodation Industry)

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
Platform Number	-0.081**	0.041	0.016	0.027
	(0.026)	(0.033)	(0.025)	(0.028)
Platform Number × Manager		-0.363***		-0.032
		(0.055)		(0.030)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	16,723	16,723	16,723	16,723
Adjusted R^2	0.885	0.886	0.795	0.795

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Table D18. Replication of Main Table (Only Including Workers in Building and Dwelling Industry)

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	0.020	0.094+	-0.004	0.017
	(0.051)	(0.053)	(0.039)	(0.040)
TaskRabbit × Manager		-0.301***		-0.088*
		(0.058)		(0.040)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	9,370	9,370	9,370	9,370
Adjusted R^2	0.771	0.772	0.654	0.655

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

D-5. Other Robustness Checks

1. Linear Time Trends

Our main model (Table 4) includes both the MSA-specific linear and quadtric time trends. To ensure the robustness of the model, we replicated the main model using only the linear MSA specific-time trend. The results are presented in Table D19, and we observe consistent results.

Table D19. Replication of Main Table by Only Using the Linear Time Trends

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.033	0.066+	0.011	0.012
	(0.026)	(0.032)	(0.027)	(0.031)
TaskRabbit × Manager		-0.294***		-0.005
		(0.058)		(0.029)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Linear Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.900	0.900	0.299	0.299

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

2. Alternative Measures for TaskRabbit Entry

The detailed entry month for TaskRabbit may also influence our main results. We further acquired the detailed entry month for each city from TaskRabbit's blog and other news websites (Table A2). We found the entry times for the majority of the cities are during the summertime, and a few of them were entered at the later time of the year. We coded treatment equal to 1 for the next calendar year if the TaskRabbit entries the city in October, November, and December. The updated results are presented in Table D20, and they are consistent with our main results.

Table D20. Estimation Results with Updated Treatment

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.068**	0.041	0.028	0.030
	(0.022)	(0.023)	(0.024)	(0.027)
TaskRabbit × Manager		-0.324***		-0.006
		(0.058)		(0.028)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.900	0.900	0.300	0.300

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

3. Lagged Effects of TaskRabbit Entry

It is possible that the effects of TaskRabbit on the number and wages of incumbent workers take time to materialize, as it takes time for companies to realize the impact of high turnover of managers over an extended time period. To further explore this possibility, we examined the lagged effect of TaskRabbit on the employment and earning of incumbent housekeeping workers for one and two years.

The results are presented in Table D21. For the lagged effect, we still observe consistent results for the negative effects on the number of middle-skilled workers. However, we do not observe lagged significant effect on the wage of middle-skilled workers.

Table D21. Lagged Impact of TaskRabbit Entry on Housekeeping Workers

	(1) Lagged 1 Year				(2) Lagged 2 Year			
VARIABLES	Number	Number	Wage	Wage	Number	Number	Wage	Wage
TaskRabbit_lag1	-0.058**	0.052*	0.024	0.025				
	(0.016)	(0.020)	(0.027)	(0.030)				
TaskRabbit_lag1 × Manager		-0.327***		-0.003				
		(0.058)		(0.026)				
TaskRabbit_lag2					-0.051+	0.064+	-0.039	-0.036
					(0.028)	(0.033)	(0.038)	(0.040)
TaskRabbit_lag2 × Manager						-0.343***		-0.007
						(0.069)		(0.029)
Time-varying Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,921	15,921	15,921	15,921	14,658	14,658	14,658	14,658
Adjusted R-squared	0.838	0.839	0.246	0.246	0.838	0.838	0.239	0.238

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

4. Moderating Role of the Share of Housekeeping Employment

It is known that TaskRabbit also offers non-cleaning tasks (e.g., moving), which may influence the measurement accuracy of our treatment variable—TaskRabbit entry.

To better isolate the effect of housekeeping services from other services, we separated our treated MSAs (by median) into two groups – a larger employment share and a smaller employment share of housekeeping occupations (over entire employment population of each MSA). The cut point is the median of housekeeping employment share between 2005-2007 prior to TaskRabbit entry. The rationale is that if the observed effects are unbiased and only caused by housekeeping services, we expect them to be more pronounced in locations with a larger labor market for housekeeping services.

The results are shown in Table D22. We observe that the negative effects on middle-skilled workers are stronger in MSAs with a larger share of housekeeping employment than in MSAs with a smaller share, further corroborating the robustness of our main findings.

Table D22. Moderating Role of Share of Housekeeping Employment

	Dependent Variables			
	ln (Number of Workers)		*ln* (Average Annual Wage)	
	(1)	(2)	(3)	(4)
TaskRabbit	-0.043	0.028	0.012	0.015
	(0.040)	(0.026)	(0.031)	(0.021)
TaskRabbit × HS Share	-0.049		0.002	
	(0.050)		(0.040)	
TaskRabbit × Manager		-0.185***		-0.015
		(0.055)		(0.039)
TaskRabbit × Manager × HS Share		-0.191**		0.018
		(0.066)		(0.040)
Time-varying Covariates	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Location-Specific Time Trends	Yes	Yes	Yes	Yes
# Observations	17,160	17,160	17,160	17,160
Adjusted R^2	0.900	0.900	0.300	0.300

Note: Time-varying covariates include population, density, income, education, sex ratio, age ratio, platform service demand, and GDP. Robust standard errors (clustered at MSA and year level) are in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

5. Interpretation and Summary of the Coefficients

In this section, we interpret the economic impact of our main analysis as shown in Table 4. Determining the precise effect magnitude in a staggered DiD setting is challenging due to potential heterogeneous treatment effects across years and different MSAs, where TaskRabbit launched at different time periods (Baker et al. 2022). Notably, we addressed this issue in §4.5.3, where estimates remain consistent, even after applying a heterogeneity robust DiD model. This suggests that the potential for heterogeneous treatment effects does not significantly bias our baseline estimates. Therefore, we assume a constant treatment effect over time to calculate the impact on the number of workers post-TaskRabbit's entry.

First, the coefficient for TaskRabbit indicates that its introduction is associated with a reduction of 7.1% (=$100 \times (e^{-0.074} - 1)$%) in the number of housekeeping workers in the treated MSAs after treatment. We further calculate the mean number of workers in treated MSA units[32] being treated, which is 15,379. To calculate the average annual reduction per MSA, we recover the potential mean number of workers in treated MSA units had TaskRabbit not entered, which would be 16,554 (=$\frac{15{,}379}{1-7.1\%}$).[33] Multiplying this by the 7.1% reduction rate yields approximately 1,175 workers.

Following the same logic, the average number reduction for middle-skilled workers in the treated units are based on (1) the mean number of middle-skilled workers from treated units in the post-treatment period, which is 2,133 and transfers to the potential average number had each of these units not been treated 2,844 (=$\frac{2{,}133}{1-25.0\%}$) and (2) a 25.0% (=$100 \times (e^{-0.288} - 1)$%) reduction to the mean number of middle-skilled workers, which in turn yields approximately 711 workers.

Finally, we summarize the coefficients of interest across all model specifications explored in this study. Our aim is to provide a credible range of estimated effects, given the direct relevance of our results to policy implications. The detailed summary is presented in Table D23 on the next page.

As observed on Table D23, the estimates of the impact of TaskRabbit on the total number of workers range from -0.041 to -0.095. For middle-skilled workers, the coefficients vary from -0.146 to -0.448.

[32] The unit here is the unit of analysis of our main model: MSA-occupation-year.

[33] The reason is that what we observed in the data should be the value after reduction.

Table D23. Sensitivity of The Effect of TaskRabbit on Number of Workers to Specification Changes

Specification	Number of workers	Number of middle-skilled workers	Sample Size
	(1)	(2)	(3)
1. Main Model	-0.074**	-0.284***	17,160
	(0.020)	(0.041)	
2. Matching (CEM)	-0.062	-0.322**	2,074
	(0.022)	(0.141)	
3. Only include treated MSAs	-0.083*	-0.286***	3,662
	(0.030)	(0.091)	
4. Exclude MSAs entered after 2017	-0.092***	-0.300***	16,275
	(0.021)	(0.074)	
5. Only include large MSAs	-0.095**	-0.290***	4,143
	(0.023)	(0.081)	
6. Exclude data period after 2017	-0.078*	-0.305***	15,957
	(0.026)	(0.089)	
7. Heterogeneity-Robust DiD Model	-0.093+	-0.448***	17,160/5,018
	(0.048)	(0.163)	
8. Generalized Synthetic Control	-0.041+	-0.146***	17,160/5,018
	(0.024)	(0.035)	
9. Include main competitors	-0.068*	-0.218**	17,160
	(0.026)	(0.072)	
10. Exclude travel accommodation industry	-0.081**	-0.322***	16,723
	(0.026)	(0.025)	
11. Only workers in building and dwelling industry	0.020 (0.051)	-0.207*** (0.046)	9,370
12. Only Include location-based linear time trends	-0.033 (0.026)	-0.228*** (0.037)	17,160
13. Alternative Measures of TaskRabbit	-0.068**	-0.283***	17,160
	(0.022)	(0.035)	
14. Lagged 1-year effect of TaskRabbit	-0.058**	-0.275***	15,921
	(0.016)	(0.044)	
15. Lagged 2-year effect of TaskRabbit	-0.051+	-0.279***	14,658
	(0.028)	(0.087)	

Notes: The coefficients for the total number of workers are directly estimated from the models. The coefficients for middle-skilled workers are based on the combination of $\beta_3 + \beta_4$ except for the heterogeneity-robust DiD model and the generalized synthetic control. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Appendix E. Empirical Extensions

In this section, we provide further empirical evidence to support the mechanisms proposed in the paper.

1. Effect of TaskRabbit Entry by Company Size
First, we provide suggestive empirical evidence on how the impact of TaskRabbit varies among incumbent middle-skilled workers in companies of different sizes. If TaskRabbit enhances operational efficiency in housekeeping businesses, smaller-sized ones are more likely to be affected due to their simpler management tasks and greater incentives to adopt TaskRabbit. Additionally, middle-skilled managers in larger companies often perform more complex tasks, such as training, in addition to matching and monitoring low-skilled workers—functions that overlap with those provided by the online gig platform, making them less likely to be substituted by the gig platform. Therefore, we would expect to observe stronger effects of TaskRabbit on incumbent workers in small-sized housekeeping companies.

Empirically, we acquired company size data from the Annual Social & Economic Supplement (ASES), and we categorized companies into three groups—small (under 10 employees), medium (10-99 employees), and large (100 or more employees). This categorization is based on the original survey structure and ensures consistency in measurement across our data periods.

The results, presented in Table E1, indicate that small-sized companies are more likely to be affected by TaskRabbit (i.e., middle-skilled workers at smaller companies are more likely to leave their companies and become self-employed; see the stronger TaskRabbit effect for small-sized firms, and also note *TaskRabbit* in Column 2 represents the baseline condition $TaskRabbit \times$ *Small-sized Firm*), compared to large-sized companies (middle-skilled workers at larger companies are less likely to leave the companies; see the weakened TaskRabbit effect for larger-sized firms), which further complement our proposed mechanism.

Table E1. Moderating Effect of Firm Size of Middle-skilled Workers

	Dependent Variables: whether an incumbent housekeeping worker (middle-skilled or low-skilled) changed status from work-for-wages employment to the following (1/0)	
Current employment status:	Self-employed (*Incorporated*) in housekeeping occupations	Self-employed (*Incorporated*) in housekeeping occupations
TaskRabbit	0.027***	0.069**
	(0.008)	(0.033)
TaskRabbit × Middle-sized firms		0.006
		(0.030)
TaskRabbit × Large-sized firms		-0.051**
		(0.021)
Middle-sized firms		-0.015
		(0.016)
Large-sized firms		-0.07
		(0.060)
Time-varying Covariates	Yes	Yes
MSA and Year FE	Yes	Yes
Location-specific Time Trends	Yes	Yes
Observations	3,465,711	3,465,711
Adjusted R-squared	0.114	0.179

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

2. Effects of TaskRabbit Entry on Working Hours and Hourly Wages

To provide a simpler and clearer mechanism, we further explored how the entry of TaskRabbit affects the working hours and corresponding productivity of work-for-wages workers. As hypothesized, if the online gig platforms help companies increase their operational efficiency and can replace some middle-skilled managerial jobs, the working hours of middle skilled workers should go down. To test this possibility, we further acquired data for working hours from IPUMS. We calculated the total working hours for the year by multiplying the number of weekly work hours by the number of weeks worked in the year. We also generated the hourly wages by dividing the annual wages by the total number of hours worked. To explore the hours changes before and after the entry of TaskRabbit, we restricted our sample to include workers who have the same employment mode and occupation in the two consecutive years. Specifically, we focused on three outcome variables – "Hours Difference", "ln(Total Hours)", and "Hourly wages".

The results, as detailed in Table E2, show that the entry of TaskRabbit significantly reduces the working hours for middle-skilled housekeeping workers. Although the coefficient for hourly wages is positive, it is not statistically significant. These results support the notion that the use of TaskRabbit enhances operational efficiency in housekeeping companies, consequently reducing the need for middle-skilled workers spending their working hours on functions (e.g., matching and supervising) overlapped with those facilitated by the online gig platform.

Table E2. Difference-in-Differences Estimation of TaskRabbit on Working Hours and Productivity

	Dependent Variables					
	Hours Difference		*ln* (Total Hours)		Hourly Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
TaskRabbit	0.222	0.268	-0.016	-0.012	-1.19	-1.212
	(0.278)	(0.283)	(0.021)	(0.021)	(1.041)	(1.059)
TaskRabbit × Manager		-0.906*		-0.097**		0.422
		(0.447)		(0.036)		(1.249)
Time-varying Covariates	Yes	Yes	Yes	Yes	Yes	Yes
MSA and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Location-specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,976,741	50,976,741	50,976,741	50,976,741	50,976,741	50,976,741
Adjusted R-squared	0.056	0.056	0.079	0.08	0.056	0.056

Notes: The dependent variable, "*Hour Difference*", represents the change in working hours between two consecutive years, calculated as the current year's working hours minus the previous year's working hours. Time-varying covariates include all 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

3. Skills Required and Risks Involved in Starting a New Venture in the Housekeeping Industry

We delve deeper into the possibility of middle-skilled workers moving to becoming self-employed (incorporated) from the following perspectives. Theoretically, we expanded our arguments on how TaskRabbit can facilitate middle-skilled managers' shift towards entrepreneurial activities, detailed on pages 15 and 16 of the manuscript. While entrepreneurial activities carry inherent risks, we argue that TaskRabbit can mitigate these risks by addressing marketing, operational, and financial challenges. This perspective is supported by several recent studies that recognized gig platforms as catalysts for entrepreneurial ventures (e.g., Barrios et al. 2020, Vallas and Schor 2020). Specifically, gig platforms can reduce risks in the following ways: (1) by optimizing the service matching process, thus reducing the expenses involved in acquiring customers and potentially decreasing market risk (Einav et al. 2016); (2) by reducing reputational risks through efficient reputation or feedback systems (Vallas and Schor 2020); and (3) by mitigating financial risk for entrepreneurs by providing income sources (Barrios et al. 2020).

Empirically, we collected information to assess the necessary skills and costs involved in starting new cleaning ventures. The findings, detailed in Tables E3 and E4, reveal that the average start-up costs are relatively manageable (mean of $3,500), and the required skills are generally within the capabilities of middle-skilled workers. Importantly, regarding the specific skills required, prior studies showed that entrepreneurial skills are predominantly learned by practicing (Iyigun and Owen 1998). For instance, research indicates that many entrepreneurs develop crucial skills, not at the outset of their careers, but rather through hands-on experience and subsequent reskilling (e.g., Cope 2005, Kozlinska et al. 2023). In conclusion, the skills and risks involved in starting a new venture in housekeeping industry are not so daunting as often expected in other industries (e.g., tech industry). The above perspectives lend credence to our findings that middle-skilled workers are likely to move to become entrepreneurial self-employed.

Table E3. Staring New Cleaning Businesses – Necessary Steps

Launching and Operating Start-ups	Approximated Costs
1. Cleaning service selection (e.g., basic cleaning, deep cleaning, etc.)	NA
2. Setup (business registration, licensing, and insurance)	$435 - $760/year
3. Cleaning supplies and equipment acquisition	Start from $100
4. Pricing and job estimation (e.g., hourly rate, flat rate, etc.)	NA
5. Marketing (e.g., websites and business cards)	Start from $150
6. Invoicing and cash flow management (e.g., payment methods, invoices)	NA
7. Client and business management (e.g., book systems, schedule jobs, etc.)	NA
8. Hiring and training new cleaners	NA

Notes: The above information is provided from: https://getjobber.com/academy/cleaning/how-to-start-a-cleaning-business/ and is based on small housekeeping businesses.

Table E4. Entrepreneurial Skills for Small Business

Skills	Contents	Examples of related skills of middle-skilled workers
Management skills and financial skills	Management skills involved general business management activities, such as short-term planning, organizing, staffing, and coordinating. Financial skills are centred on creating accurate cost estimates and setting prices to ensure the business operates profitably.	• Scheduling cleaning services, • Evaluating cleaners' performance, • Pricing and job estimation.
Marketing skills	Marketing skills include defining the target, identifying one's competitive advantage, and identifying and pursuing marketing channels.	• Targeting potential clients, • Increasing visibility, • Advertising services.
Personal maturity	Personal maturity encompasses the development of emotional intelligence, resilience, and reliable judgment, often reflecting in self-awareness and adaptability.	• Handling customer feedback properly • Demonstrating patience and strategic planning
Organizational development skills	Organizational development skills encompass activities involved in developing the organization capital of the business and overcoming barriers to the growth of the business.	• Team building • Training new cleaners

Notes: Adopted from Dahlstrom and Talmage (2018) and O*Net data base.

Appendix F. Literature Review

Table F1. A Brief Literature Review of Gig Platform Related Studies

Authors (Year)	Topic	Platform	Key Findings
Cramer and Krueger (2016)	This paper compares the efficiency (capacity utilization) between ride-sharing services and traditional taxi services.	Uber	UberX drivers spend a significantly higher fraction of their time, and drive a substantially higher share of miles, with a passenger in their car than taxi drivers.
Hall and Krueger (2018)	This paper analyzes the labor market for Uber's driver-partners	Uber	Uber has attracted driver-partners with a wide range of backgrounds because they value the type of opportunity
Berger et al. (2018)	This paper examines the impacts of Uber on the employment of workers in traditional taxi services.	Uber	Uber reduces the earnings potential of incumbent drivers in traditional taxi services while does not influence their labor supply.
Burtch et al. (2018)	This paper explores the impact of gig economy platforms on local entrepreneurial activity.	Kickstarter	Gig-economy platforms predominantly reduce lower-quality entrepreneurial activity.
Schwellnus et al. (2019)	This study explores the impact of gig economy platforms on incumbent workers.	Multiple	The entry of gig economy platforms has had no discernible impact on the number of incumbent workers.
Li et al. (2021)	This paper studies the impact of the entry of Uber on the supply and demand sides of the labor market.	Uber	The introduction of the ridesharing platform increases the labor force participations while reducing the number of incumbent low-skilled workers.
This Study	Our study explores the impact of the entry of gig platforms (i.e., TaskRabbit) on the supply of incumbent workers and the heterogenous effects by skill.	TaskRabbit	The introduction of gig platforms redistributes incumbent middle-skilled workers into self-employment.

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