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The Impact of the Gig Economy on Product Quality Through the Labor Market: Evidence from Ridesharing and Restaurant Quality

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Abstract. This paper seeks to demonstrate the impact of the gig economy on product quality in seemingly unrelated local industries through the labor market. Our empirical context is the quality of service for restaurants in the city of Austin, and we examine how they were impacted by the *exogenous* exit and reentry of rideshare platforms, Uber and Lyft, because of regulatory changes. We leverage these exogenous shocks and combine them with sentiment-analyzed data from Yelp reviews that capture how customers assess the quality of service at each restaurant. We show that, compared with control cities, customers in Austin become more negative about service quality when Uber and Lyft are present in the city. Additionally, we use rich data on employee turnover and wages to demonstrate that service staff turnover increases in Austin when Uber and Lyft are present compared with the control cities. We also conduct several additional studies and robustness checks that are all congruent with our hypothesis that Uber and Lyft lower the quality of service in Austin restaurants by raising their staff turnover. Together, these results suggest significant ramifications of the gig economy on the broader industries through the labor market.

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1. Introduction

How does restaurant quality change when Uber and Lyft, large rideshare companies, enter the market? The gig economy has significantly transformed the landscape of several industries. For instance, rideshares such as Uber and Lyft alter the way people use public transportation and taxis. Airbnb challenges existing hotel chains and has revolutionized the lodging market. What may not be so obvious, though, are the less direct impacts of the gig economy in local economic markets. Take, for example, the restaurant industry. Could restaurant quality be related to whether ridesharing companies operate?

One naturally expects, if there is a relationship, the main channel for the impact of rideshares such as Uber and Lyft on the local restaurant to be through the mobilization of demand. In this paper, however, we investigate a different mechanism: labor market. Uber's and Lyft's presence in a city may take away labor from people who would have otherwise chosen to work at a restaurant.[1] Despite the large number of people currently employed by restaurants, the industry is facing a shortage of workers.[2] This concern is unlikely to go away: as it becomes easier to arrange short-term labor contracts, rideshare services will continue to grow, providing alternative work arrangements for low-wage, low-skill workers. Katz and Krueger (2019) find that these types of work arrangements rose from 10.1% in February 2005 to 15.8% in late 2015.[3] And, while the restaurant industry may not be unique in its struggle to hire enough workers, its position as the second largest job provider in the United States speaks to its significance.[4]

Whereas independent or contract work is hardly a new phenomenon, the advance of digital technologies has spurred tremendous growth of the gig economy in the current labor market. The Bureau of Labor Statistics reported in 2017 that 55 million people in the United States, accounting for approximately 34% of the workforce, are gig workers. This figure is projected to increase to 43% in 2020.[5] This opens a significant new opportunity for low-skill laborers. The labor economics literature studies this phenomenon that workers with low pay and/or inflexible schedules are "poached" by Uber and Lyft (Katz and Krueger 2017, Hall and Krueger 2018, Chen et al. 2019), and industry reports confirm this trend for restaurant employees[6] with the exception of management-level workers.[7]

This paper seeks to demonstrate the impact of the gig economy on the local economy beyond directly related incumbent industries through the labor market. We look at the restaurant industry as a case study. We design our analysis around a natural experiment in which, because of regulatory shifts, Uber and Lyft exited the market in Austin, Texas, in May 2016 and returned in May 2017. Leveraging this *exogenous* exit and reentry, we conduct a series of analyses to study the relationship between rideshare and restaurant quality. More specifically, we are interested in examining the following hypothesis: the presence of Uber and Lyft in a city provides individuals with gig work opportunities. Such opportunities regularly poach individuals working in the service industry, thereby increasing the turnover rate at these businesses—restaurants in our case. This increase in turnover adversely impacts the quality of service they can offer.

We first establish the relationship between the presence of ridesharing companies and restaurant quality by analyzing how the quality of restaurant service in Austin responds to the presence of Uber and Lyft. We compare Austin's response to the control group of Dallas. We use every Yelp review of restaurants in Austin and Dallas from 2014 to 2019 to measure quality. This entails text analysis of each review to capture restaurant quality along two dimensions: service and food. Leveraging a difference-in-difference (DiD) setting, we show that the quality of service decreases in Austin relative to Dallas with the presence of Uber and Lyft. Also, we carry out our main analysis a second time looking at customer satisfaction with food quality rather than service quality as our dependent variable. We hypothesize that customer experience with the food quality is less influenced by the presence of Uber and Lyft than is the service quality. Employees in charge of the food quality, such as chefs working in the kitchen, are not much attracted by the opportunity to drive for Uber and Lyft relative to workers, such as waitstaff, mostly dealing with the service for customers. We demonstrate that the customer evaluation of food quality does not change before and after Uber and Lyft's reentry to Austin.

Moreover, we divide restaurants into two tiers based on pricing labels provided by Yelp. One group consists of restaurants that are assigned a single dollar sign in Yelp, meaning they are cheaper. The rest of the restaurants, those with two or three dollar signs, comprise the second group. Workers in low-tier restaurants are paid less because either their base hourly wage is lower or their tipped income is lower. Therefore, we expect Uber and Lyft's impact to be more pronounced for single-dollar-sign restaurants whose service workers are more likely to be lured by gig work opportunities. Our empirical analysis indeed confirms this expectation. We show that the effect of Uber and Lyft in Austin on service quality is significant for single-dollar-sign restaurants. In contrast, we do not find any significant effect for high-tier restaurants.

Next, we directly test our mechanism by examining turnover rates of staff at restaurants by leveraging a unique worker-level data set of restaurants in Austin and Dallas from 2014 to 2019. We examine how the turnover rate of staff in Austin's restaurants changes with the local activity of Uber and Lyft in a DiD manner, using Dallas as the control group. We show that the turnover rate increases in Austin relative to Dallas after Uber and Lyft return. Additionally, in the same spirit as the dollar-sign analysis in Yelp data, we use the restaurant category information in the data set to examine whether we see a similar pattern in the turnover rates for different restaurant categories. If our hypothesis is correct, we expect the effect of Uber and Lyft on turnover rates to be stronger for low-end restaurant categories than relatively high-end restaurants. We conduct separate DiD analyses for each category and indeed find an increase in turnover only for low-end restaurants. In contrast, we do not see such a pattern for middle- or high-end restaurants.

We then delve deeper into the analysis by decomposing the turnover rates into turnover rates for back- (BOH) and front-of-house (FOH) staff. The latter group represents those who directly deal with customers and consists mainly of service staff, whereas the former includes higher paid positions such as managers and chefs. The results are consistent with the Yelp review data analysis: the increase in turnover is observed only for front-of-house workers, whereas there is no significant effect for back-of-house staff.

Finally, we check our analysis by conducting several robustness checks and discuss other alternative explanations based on demand-side channels. One expects some other channels through which the rideshare companies could have impacted the local economy, such as the demand changes because of the easier mobilization. Whereas we cannot completely rule out all possible explanations, we show that these alternative accounts cannot fully explain the patterns observed in our data. Also, we present other evidence suggesting that our findings are more likely to arise from the supply-side channel through the labor market rather than the demand-side channels.

Whereas this work focuses exclusively on the restaurant industry, we consider it to be a useful case study for a wider set of industries and believe that our findings can provide important insights for the economy as a whole. Faced with the entry of Uber and Lyft, policy discussions typically focus on effects on incumbent industries in clear competition: taxis and other forms of public transportation. This work, however, shows that the expansion of the gig economy, by providing new work opportunities for low-wage, low-skill workers, has far-reaching and significant ramifications on broader industries through the labor market. This effect can be especially pronounced for those gig work professions that require minimal qualifications (such as rideshare, which basically requires a car and a driver's license).

The paper is organized as follows. In Section 2, we discuss the related literature. Section 3 explains our basic hypothesis based on labor market mechanisms and describes the data. In Section 4, we analyze the effects of the rideshare economy on the restaurant industry using Yelp review data, and we present the basic results from DiD analysis. Section 5 presents the direct evidence utilizing the restaurant employee turnover data. In Section 6, we provide additional robustness checks of our main analysis along with discussions about alternative explanations and limitations of the current research. Section 7 concludes.

2. Related Literature

This paper contributes to several related areas on the effects of the gig economy, the impact of employee turnover, and the sentiment analysis of customer review data. First, our paper is closely related to a growing literature on the gig economy. There are several papers that document the impacts of the gig economy on the directly related industries. Barron et al. (2021) investigate the influences of Airbnb on housing prices and rents. Cramer and Krueger (2016) show that Uber drivers serve more passengers than traditional taxi drivers because of efficient matching technology and flexibility benefits. Berger et al. (2018) document that traditional taxi drivers experience about a 10% decline of their earnings after the entry of Uber.

A large body of recent papers investigates the consequences of the gig economy, focusing on the demand-side impacts for various sectors. For instance, they study how the rise of rideshare companies changes demand for public transportation (Di et al. 2019) and for lodging (Zhang et al. 2022) and housing properties (Gorback 2020). In addition to rideshare companies, researchers investigate the impacts of other forms of the gig economy, such as examining how Airbnb affects demand for an apartment rental (Barrios et al. 2012), hotels (Zervas et al. 2017), and home values (Jefferson-Jones 2015).

Another stream of research in the gig economy literature studies the indirect impact of the gig economy, focusing on the supply-side effects. Chen et al. (2019) analyze the value of flexibility that the gig economy provides to its workers. Hall and Krueger (2018) show that only 8% of Uber drivers are unemployed before they start driving with Uber, suggesting that many workers indeed switch their job to rideshare companies. These results are consistent with other research that finds a positive relationship between local unemployment level and the labor supply in the gig economy (Katz and Krueger 2017).

Our paper is in line with these studies in that we also investigate the supply-side effects of the gig economy. However, these studies do not examine how the labor market consequences of the gig economy, in turn, shape the performance (i.e., the quality of the products/services) of the impacted firms. This is the gap we aim to bridge in this paper.[8] Also, most literature focuses on the impact of the gig economy on the relevant service categories through direct competition (e.g., Barron et al. 2021, investigating Airbnb's influences on housing prices and rents). In contrast, this study shows that the rideshare services may make broader economic impacts through the labor market beyond the direct competition with other transportation services. Therefore, this paper makes an important contribution to the literature, suggesting that the presence of the gig economy may broadly influence the service quality of other service industries through labor market stability (e.g., turnovers, wages, etc.). We deliver specific insights regarding the implications of it. For instance, we show that the effect of rideshare companies is significant on the perceived quality of service but not on that of food.

Also, our work builds on previous literature that focuses on the causal relationship between customer satisfaction and profitability, which is a topic of ongoing academic and managerial interest (Sasser et al. 1997, Estelami 2000). Several studies show a strong relationship between employee turnover and firm performance metrics, such as sales and profits (Hancock et al. 2013, Holtom and Burch 2016) based on the role of sales service (Shin 2005) and demonstrate how employee turnover can lead to lower customer satisfaction (Koys 2001). This stream of research helps conceptualize the consequences of employee turnover on customer satisfaction and firm profit, connecting knowledge residing within employees and organizational performance (Kim 1993, Hurley 2002). For example, Schneider and Bowen (1993) report that higher levels of employee turnover can lead to lower levels of customer satisfaction in retail stores. High employee turnover may be reflected in the loss of experienced employees and established customer relationships, resulting in negative effects on customer satisfaction. Our analysis confirms these theoretical and empirical results, making a connection between employee turnover and customer satisfaction about a restaurant's service quality.

Finally, regarding data and methodology, this paper belongs to the growing literature that draws managerial and policy insights by text analysis on customer review data (Glaeser et al. 2018, Lee et al. 2018). Some recent papers in business strategy and marketing, such as Chakraborty et al. (2022) and Farronato and Zervas (2019), examine more accurate attribute-level sentiments of customer reviews using a machine learning approach. In a similar vein, we use review texts to extract customers' sentiment information about separate aspects of restaurant quality, such as service and food. We show that, in line with our hypotheses, it is indeed crucial to separately capture the evolution of the customer sentiment for each of these attributes.

3. Empirical Setting, Main Hypotheses, and Data

3.1. Empirical Setting: Natural Experiment in Austin 2016–2017

We design our analysis around a natural experiment in which Uber and Lyft exited the local market in May 2016 and returned in May 2017 in Austin, Texas, because of regulatory policy changes. The fact that both the exit and reentry happened purely because of legal reasons rather than economic ones[9] allows us to interpret them as exogenous shocks to the economic environment that we study. This is in contrast to most previous studies, which examine the economic effect of rideshare by relying on an analysis of *endogenous* entry (e.g., Gorback 2020, Barrios et al. 2022).

Figure 1 describes the timeline of Uber's and Lyft's presence and absence in Austin. It can be seen from this figure that there are two possible natural experiments: May 2016 when the two rideshare companies exit the city and then May 2017 when they return. It is interesting to note that both of these events could, in principle, be leveraged as the shock for studying the impact of rideshare on the rest of the economy. As we show later in our analysis, however, all of our analyses find a weaker effect of the first event, whereas we find a much stronger effect of the second event. Therefore, we believe, it is likely that the effect of the first event was mitigated because of some factors. Though we do not take a firm stance on what those mitigating factors may be, we point out the following several possibilities.

First, we note that higher employee turnover can lead to decrease in service quality in two ways: (i) by reducing the number of restaurant workers (shortage of workforce *quantity*) and (ii) by reducing the workforce *quality*. Higher turnover can imply a lack of adequate experience or training for the average worker, which eventually decreases the service quality.[10] Therefore, the effect of Uber/Lyft entry, which entails high turnover of restaurant servers, can be immediate on the service quality, whereas the effect of Uber/Lyft exit, which may lead to an increase in restaurant servers, may be gradual because of the learning curve.[11]

Second, it could be that the size of the second shock to the market might be substantially larger than the first one. Hall and Krueger (2018) document the exponential growth pattern in the number of Uber drivers in the United States from mid-2012. These patterns are consistently observed in most U.S. cities in their studies (e.g., figure 3 in Hall and Krueger 2018). Thus, we conjecture that Uber and Lyft were substantially larger (in terms of the number of rides they gave) in May 2017 compared with May 2016, which might cause the asymmetric impacts of these two shocks. Another possibility is the potential asymmetry in labor mobility. Jackson (2020) shows that individuals who worked for the gig economy are less likely to return to traditional jobs. Flexible gig work experience, such as driving Uber or Lyft, might change workers' job preference. Thus, those workers may not necessarily go back to traditional workplaces, such as restaurants, even after Uber and Lyft left the city. They might search for other jobs that are more flexible.

Based on this, our discussions focus, for the most part, on the second event (i.e., the return of the rideshare platforms to the city).

3.2. Main Hypotheses

The primary focus of our research is to empirically test whether Uber's and Lyft's presence in Austin reduced the service quality of restaurants through an

Figure 1. (Color online) Timeline of a Natural Experiment in Austin

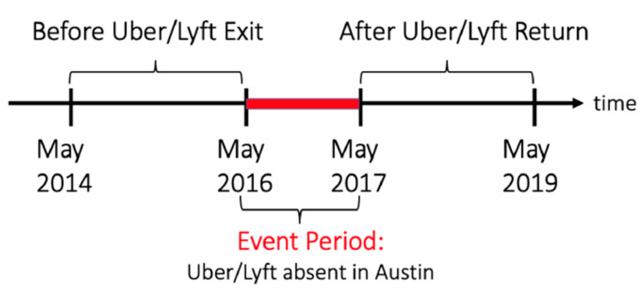
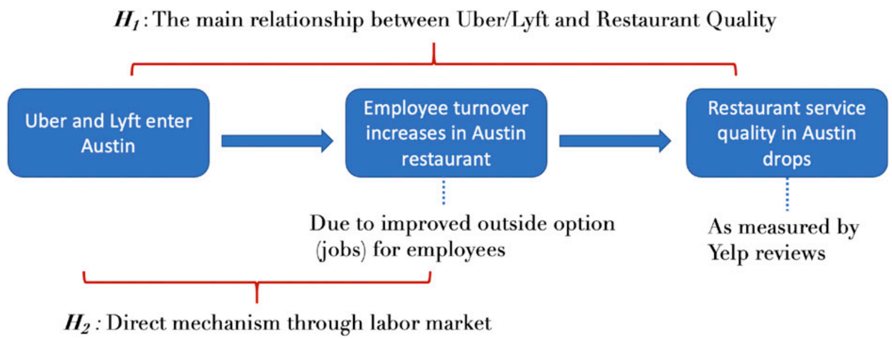


Figure 2. (Color online) Two Main Hypotheses to Test.



Notes. Hypothesis 1: Uber's and Lyft's return to Austin led to a drop in the service quality as measured by Yelp reviews. Hypothesis 2: Uber's and Lyft's return to Austin increased employee turnover at restaurants.

impact on the employee turnover in those restaurants. This translates to two main hypotheses to test.

Hypothesis 1. *Uber's and Lyft's presence in Austin led to a decrease in the service quality provided by those restaurants.*

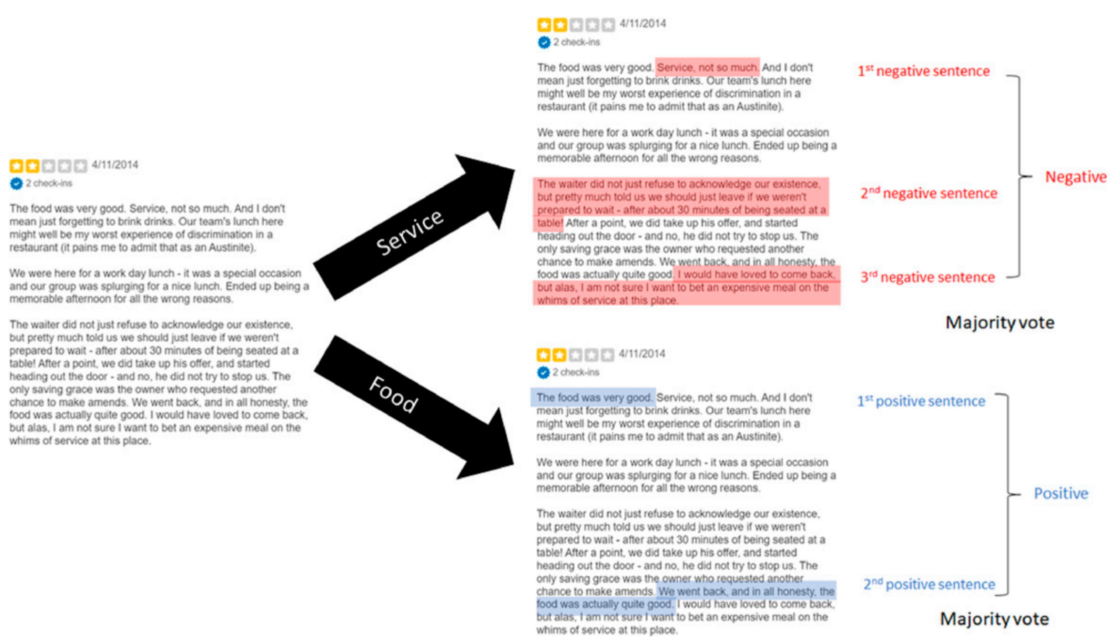
Hypothesis 2. *Uber's and Lyft's presence in Austin led to an increase in the employee turnover for the city's restaurants.*

Figure 2 schematically illustrates the relationship between Hypotheses 1 and 2. After empirically establishing the relationship between Uber's and Lyft's presence and the restaurant's service quality utilizing the natural experiments in Austin areas (Hypothesis 1), we further explore the mechanism underlying this relationship through formally investigating Hypothesis 2. Our mechanism is based on employee turnover. If Hypothesis 2 is correct, one expects that an increase in the employee turnover for Austin's restaurants must have led to a decrease in the service quality provided by those restaurants (Hancock et al. 2013, Holtom and Burch 2016).

The combination of Hypotheses 1 and 2 lends itself to a clear conceptualization of the analysis done in this paper. However, in principle, it is possible that the presence of Uber and Lyft in the city can bring about other economic changes which, then, led to a drop in restaurant service quality. In Section 6.2, we discuss some of those possible alternative channels through which Uber and Lyft can influence restaurant service quality, and we argue that there is evidence they do not have a major impact.

In the remainder of the paper, when both describing our data and conducting the empirical analysis, we start examining by Hypothesis 1, which pertains to the *overall impact* of rideshare on service quality. We

Figure 3. Illustration of Review-Level Classification by Attribute



then turn to Hypothesis 2, which pertains to the study of our proposed *mechanism* through which the impact happens. We now turn to the construction of our data for this analysis.

3.3. Two Data Sets: Yelp Reviews and Employee Turnover

In order to test Hypothesis 1, we need a measure of service quality for restaurants in Austin and possible control cities. We obtain this measure by text analysis of Yelp reviews written for restaurants in Austin and other cities during the time span of our empirical analysis.[12] As we describe later, we also use similar methods to obtain quality measures for attributes other than service (e.g., food). In order to study Hypothesis 2, we leverage detailed data on employee turnover at restaurants in Austin and our control city. We use Dallas as our main control city based on similarities in macroeconomic conditions.[13] In Section 6.1, we conduct a series of robustness checks by, among others, (1) conducting a parallel trend analysis between Austin and Dallas and (2) using another similar city in Texas, San Antonio, as a new control city instead of Dallas. All of these checks show the robustness of our results. We describe these two data sets in further detail.

3.3.1. Yelp Review Data.

3.3.1.1. Overview. The unit of observation in our Yelp review data is restaurant-month. For each restaurant i in Austin (and our control city, Dallas) during each month t between May 2014 and May 2019, we construct multiple measures, including how many Yelp reviews were written for a restaurant i during the month of t, how many of them were overall negative (or positive) about service, and how many of them were negative (or positive) about food. We also have information on the overall price tier of each restaurant provided by Yelp using one dollar sign ($) for cheap restaurants, two dollar signs ($$) for mid-tier ones, and three dollar sign ($$$) for expensive restaurants. In addition, we have information on the type of food/service each restaurant offers provided by Yelp such as “bar,” “sushi,” “breakfast,” and so on.

We apply some filters to construct our final data set. First, we choose reviews written between May 2014 and May 2019, covering a window from two years before Uber and Lyft’s exit from Austin to two years after their return. Second, to minimize potential confounding effects from the entry or exit of restaurants, we discard data from restaurants whose first review date is after May 2016 and drop restaurants whose last review date is before May 2017. We also find that a few restaurants in our original sample do not get even one review per month. So we add the last rule to select restaurants whose total number of reviews in our sample period is bigger than 200 (at least three reviews per month on average).[14]

3.3.1.2. Construction. Part of our data come in a format that cannot be directly used for our analysis: each review is a short or long text describing a customer’s experience at a restaurant. What we need, however, is an indicator specifying whether the review is referring to a specific attribute of the restaurant (such as service and food) and whether that review is positive, negative, or neutral toward that attribute of the restaurant. As a result, we carry out some processing on the data.

To be precise, our processing of the text data has three main steps. We explain the procedure for service. It is similar for other attributes, such as food. The first step is to take each sentence and then decide whether that sentence is related to the attribute of interest (such as service or food.) We arrive at this decision for each sentence by checking whether that sentence contains any of the words in our predefined dictionary of words that have to do with service or food (Taddy 2013).

The second step takes each sentence and specifies whether the sentiment of that sentence is positive, negative, or neutral. For this task, which is the building block of our algorithm, we use a lexicon-based method (Taboada et al. 2011) to assign sentiment scores to sentences. On a high level, this approach looks at the sentence word by word and assigns a positive or negative sentiment score to each relevant word. The score for each word is determined by (i) reading the score for that word off of a predefined dictionary and (ii) applying multipliers in order to correct for “valence shifters” such as negations, intensifications, and down-toners. Ultimately, a sentiment score is assigned to each sentence.

Finally, equipped with a method to score sentiments of individual sentences, we arrive at the sentiment for the entire review. Similar to the literature (e.g., Berger et al. 2010), we use a majority vote rule by which the overall sentiment index is the same as the score with more occurrences. The overall index can take three possible values: negative, positive, or neutral if the sum of the scores for the components of the sentence is, respectively, strictly negative, strictly positive, or equal to zero.[15] Figure 3 shows an illustration of how our algorithm assigns a service- or food-specific sentiment score to a review. As can be seen from this figure, the same review is classified as positive regarding food but negative regarding service.

3.3.1.3. Summary Statistics. Table 1 shows some descriptive statistics for Yelp review data. It provides summaries at the review and restaurant level for the cities of Austin and Dallas and for three periods: before Uber and Lyft left the city (i.e., May 2014–April 2016),

Table 1. Summary Statistics in Yelp Data

Restaurant level	Total	Before (2014/May–2016/Apr)	Event (2016/May–2017/May)	After (2017/June–2019/May)
Austin, Texas				
Number of restaurants	632	632	632	632
One-dollar-sign restaurants	328	328	328	328
Two-dollar-sign restaurants	278	278	278	278
Three-dollar-sign restaurants	26	26	26	26
Monthly number of reviews per restaurant				
Average (*SD*)	5.5 (6.8)	6.1 (7.0)	5.4 (6.1)	5.3 (6.9)
Minimum	1	1	1	1
Maximum	112	85	71	112
Dallas, Texas				
Number of restaurants	504	504	504	504
One-dollar-sign restaurants	81	81	81	81
Two-dollar-sign restaurants	382	382	382	382
Three-dollar-sign restaurants	41	41	41	41
Monthly number of reviews per restaurant				
Average (*SD*)	6.6 (6.5)	6.9 (6.5)	6.6 (6.1)	6.5 (6.8)
Minimum	1	1	1	1
Maximum	110	104	95	110

Review level	Total	Before (2014/May–2016/Apr)	Event (2016/May–2017/May)	After (2017/June–2019/May)
Austin, Texas				
Number of reviewers	72,331	30,828	19,746	36,372
Number of reviews	168,086	68,484	34,544	65,058
Percentage of reviews related to service	0.560	0.561	0.559	0.561
Percentage of reviews related to food	0.714	0.721	0.710	0.709
Review rating				
Average (*SD*)	3.86 (1.36)	3.87 (1.29)	3.85 (1.37)	3.85 (1.42)
Sentence Length of each review				
Average (*SD*)	7.6 (6.1)	8.1 (6.6)	7.4 (5.9)	7.2 (5.6)
Dallas, Texas				
Number of reviewers	87,576	37,737	22,736	44,357
Number of reviews	201,910	84,582	38,930	78,398
Percentage of reviews related to service	0.572	0.569	0.572	0.574
Percentage of reviews related to food	0.781	0.791	0.779	0.773
Review rating				
Average (*SD*)	3.96 (1.28)	3.95 (1.22)	3.93 (1.30)	3.96 (1.33)
Sentence length of each review				
Average (*SD*)	7.7 (6.2)	8.3 (6.7)	7.6 (6.0)	7.2 (5.6)

during the time that Uber and Lyft were gone (i.e., May 2016–May 2017), and after the two rideshare platforms returned to the city (i.e., June 2017–May 2019).

3.3.2. Employee Turnover Data.

3.3.2.1. Overview. Our second data set contains detailed information on employees of different restaurants in Austin and Dallas. The unit of observation is employee-month. For each employee n during month t, we observe, among other things, an ID for the restaurant at which the employee worked during that specific month, job title (e.g., sous chef), and average hourly wage.[16] This information allows us to calculate how long exactly each worker stayed with a given restaurant.

We do not observe restaurant names in this data set, which prevents us from being able to merge this data set with our Yelp reviews data set. However, we do observe a restaurant category variable based on partitioning restaurants into quick service, fast casual, casual dining, upscale dining, and fine dining. Observing these categories allows us to draw parallels to the categorization on Yelp based on the number of dollar signs.[17] This, in turn, allows for analyses that parallel some of Yelp data regressions.

3.3.2.2. Summary Statistics. Table 2 summarizes the turnover data. The format in which the table summarizes the data follows how we summarized the Yelp reviews data.

Having introduced our two data sets, we turn to the empirical analysis next. We start by studying Hypothesis 1 using Yelp reviews data and then move to examining Hypothesis 2 using our employee turnover data and provide several robustness checks.

4. Analysis of Yelp Review Data

In this section, we conduct a series of analyses to study how the gig economy impacts the service quality of restaurants (Hypothesis 1), taking advantage of the exogenous exit and reentry of rideshare companies (Uber and Lyft) from and to the transportation market of the city of Austin. We conduct three different analyses to examine this hypothesis.

4.1. Quality of Service: Main Analysis

Our first analysis studies how the quality of service provided by restaurants in Austin responds to the presence of Uber and Lyft. We compare Austin's response to that of our control city, Dallas. Leveraging a DiD setting, we show that the quality of service—measured by Yelp review sentiments—decreases in Austin relative to Dallas with presence of Uber and Lyft in the city.

We consider the following DiD regression equation using the Yelp reviews data in both Austin and Dallas between May 2014 and May 2019:

$$Y_{it} = \alpha_i + \tau_t + \beta_1 \cdot I(t \in \text{Before}) \cdot I(i \in \text{Austin}) + \beta_2 \cdot I(t \in \text{After}) \cdot I(i \in \text{Austin}) + \epsilon_{it}. \tag{1}$$

In this equation, index i represents a restaurant and t indexes a month. α_i and τ_t represent restaurant and month fixed effects, respectively. An indicator variable in the interaction term, $I(t \in \text{Before})$, is a binary variable that assumes the value of one only if t happens before May 2016 when Uber and Lyft left the city of Austin. Similarly, an indicator variable, $I(t \in \text{After})$, is a binary variable that assumes the value of one only if t happens after May 2017 when Uber and Lyft reentered Austin. Note that these two indicators are not collectively exhaustive. During all months t after May 2016 but before May 2017, the two rideshare companies were absent from the city's transportation system. Also, ϵ_{it} is the error term. Finally, our dependent variable Y_{it} represents the customers' perception of restaurant i's service quality during month t. The measurement is carried out as described in detail in Section 3.3. It records the percentage of Yelp reviews written about restaurant i in month t that were negative about the service quality. Formally,

$$Y_{it} = \frac{\text{\# of negative reviews about service in month } t}{\text{total \# of reviews about service in month } t}. \tag{2}$$

As we discuss earlier in Section 3.1, there are two potential natural experiments: the moment when the two rideshare companies exit the market and when they return. So we are interested in coefficients β_1 and β_2, which show how Uber's and Lyft's presence in Austin affects the quality of service in Austin restaurants relative to Dallas restaurants before Uber and Lyft exit the market (β_1) and after they return to the market (β_2), respectively. Table 3 reports the regression results. Each of the four columns in Table 3 represents different specifications regarding the fixed effects. The first regression includes dummy variables for city (Austin) and the two periods (before the exit and after the return) along with two interaction terms with the Austin dummy. Given that the data are in panel form, we allow for a fixed effect for time (column (2)), for restaurant (column (3)), and for both (column (4)). In all specifications with restaurant fixed effects, we cluster standard errors at the restaurant level following the discussion by Bertrand et al. (2004). The same robustness check with regard to fixed effects is carried out in all of our analyses (for both Yelp reviews and employee turnover).

As this table shows, β_1 is not significant under specifications in columns (1)–(4). We do not find any effect of Uber's and Lyft's exiting the city. In contrast, we find a consistently significant effect of β_2, suggesting that the size of the second shock to the market was substantially larger than the first one. Uber's and Lyft's return to Austin increases the likelihood of a negative review on service quality by about 1.5 percentage points, which is close to 10% given the base value of 16 percentage points (column (1)). This is in line with our hypothesis. Note that the result is robust to including restaurant and/or monthly fixed effects (columns (2)–(4)). These columns show that our positive estimate for β_2 does not arise from the possibility that restaurants with worsening service in Austin got more reviews (and, hence, a higher weight) after reentry of Uber and Lyft. Rather, robustness to fixed effects shows that restaurants in Austin were more likely to receive reviews complaining about service after Uber and Lyft returned to the city. From now on, we focus on the regression with both fixed effects specification (in column (4)) for our discussion on the estimation results.

With this analysis in hand, we next delve deeper into the mechanism by which the gig economy impacts local economies.

4.2. Service vs. Food

Next, we carry out a similar study but with a focus on food quality instead of service quality as the dependent variable. If our hypothesis is correct, the presence of Uber and Lyft influence customer experience with the food quality less than with the service quality. We expect that employees in charge of the food quality, such as chefs who tend to be better paid and have more promising careers in the restaurant industry relative to waitstaff who are mostly in charge of service,[18] will be less affected by the opportunity to

Table 2. Summary Statistics in Turnover Data

Restaurant level	Total	Before (2014/May–2016/Apr)	Event (2016/May–2017/May)	After (2017/June–2019/May)
Austin, Texas				
Number of restaurants	233	233	233	233
- Quick service	21	21	21	21
- Fast casual	103	103	103	103
- Casual dining	79	79	79	79
- Upscale casual	23	23	23	23
- Fine dining	9	9	9	9
Average (*SD*) of workforce size				
- Quick service	21.4 (6.2)	23.4 (6.4)	22.5 (5.2)	18.3 (5.2)
- Fast casual	13.0 (14.1)	10.6 (11.0)	10.7 (11.3)	13.2 (14.6)
- Casual dining	25.2 (21.4)	25.2 (22.5)	25.9 (21.8)	25.7 (21.4)
- Upscale casual	43.9 (27.8)	37.5 (23.8)	44.0 (29.7)	41.1 (24.6)
- Fine dining	19.3 (7.7)	15.4 (5.3)	16.9 (5.5)	19.3 (7.7)
Dallas, Texas				
Number of restaurants	264	267	266	266
- Quick service	3	0	0	3
- Fast casual	67	67	67	67
- Casual dining	166	166	166	166
- Upscale casual	30	30	30	30
- Fine dining	1	1	0	0
Average (*SD*) of workforce size				
- Quick service	9.4 (2.8)	NA	NA	9.4 (2.8)
- Fast casual	17.9 (11.5)	17.1 (10.4)	17.6 (11.0)	17.9 (11.5)
- Casual dining	21.7 (11.4)	21.5 (11.1)	21.6 (11.2)	21.8 (11.3)
- Upscale casual	49.7 (32.0)	42.2 (22.8)	49.7 (32.0)	47.1 (31.4)
- Fine dining	33.0 (4.2)	33.0 (4.2)	NA	NA

Worker level	Total	Before (2014/May–2016/Apr)	Event (2016/May–2017/May)	After (2017/June–2019/May)
Austin, Texas				
Hourly wage ($)				
Average (*SD*)	11.8 (3.2)	10.8 (3.2)	11.7 (3.4)	12.2 (2.9)
Minimum	7.0	7.0	7.0	7.0
Maximum	28.8	28.4	28.8	28.2
Tenure (month)				
Average (*SD*)	5.1 (5.6)	4.8 (5.7)	5.3 (5.8)	5.1 (5.8)
Minimum	1	1	1	1
Maximum	60	60	36	24
Dallas, Texas				
Hourly wage ($)				
Average (*SD*)	11.9 (3.8)	11.3 (3.6)	12.3 (4.1)	12.2 (3.9)
Minimum	7.0	7.0	7.0	7.0
Maximum	30.0	30.0	29.7	29.9
Tenure (month)				
Average (*SD*)	6.0 (5.4)	6.1 (5.5)	6.0 (5.5)	6.1 (5.4)
Minimum	1	1	1	1
Maximum	60	60	36	24

Notes. The sample that we use in our turnover analysis consists of 553,404 worker-month-level observations. Workforce size refers to the number of workers in each restaurant each month. Tenure of each worker is calculated based on the start time of employment and the exit time. In addition, to make the comparison across periods more meaningful, tenure-related statistics are calculated based on workers who quit within two years since the start time of employment.

drive for Uber and Lyft relative to workers such as waitstaff.

We conduct the same DiD analysis in Equation (1) but with a different dependent variable, a measure of food quality. The results are reported in Table 4. It shows that β_2 (which captures the effect of Uber's and Lyft's return to the city on the food quality) become nonsignificant as a result of our change in the dependent variable in all of the estimated models. Thus, it confirms our hypothesis and demonstrates that indeed

Table 3. Difference-in-Difference (Service)

	Dependent variable: *Ratio of complaints on service*			
	(1)	(2)	(3)	(4)
Constant	0.161***			
	(0.002)			
Austin dummy	0.017***	0.016***		
	(0.005)	(0.005)		
Before Uber/Lyft exit	−0.001		−0.003	
	(0.003)		(0.003)	
After Uber/Lyft return	−0.001		−0.002	
	(0.003)		(0.003)	
Austin dummy × Before Uber/Lyft exit	0.005	0.006	0.006	0.008
	(0.006)	(0.006)	(0.006)	(0.006)
Austin dummy × After Uber/Lyft return	0.015***	0.017***	0.013**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
Monthly fixed effect	N	Y	N	Y
Restaurant fixed effect	N	N	Y	Y
Observations	58,227	58,227	58,227	58,227
R^2	0.003	0.004	0.130	0.131
Adjusted R^2	0.002	0.003	0.113	0.113

Note. Standard errors are clustered at restaurant level.
**$p < 0.05$; ***$p < 0.01$.

Uber's and Lyft's return to Austin does not lead to a change in customer satisfaction with food quality.

This is the first piece of evidence for our hypothesis regarding the mechanism through which the presence of rideshare companies in Austin affects the quality of restaurants. Our proposed mechanism is based on the labor market. We hypothesize that the food quality is less influenced by the presence of Uber and Lyft than the service quality because of the different natures of the two labor forces for the front- and the back-of-the-house labor. Employees in charge of the food quality, such as chefs working in the back-of-the-house kitchen, are less likely to consider the opportunity to drive for Uber and Lyft relative to workers such as waitstaff. This is in line with the observation from Tables 3 and 4 that the effect is significant only for the service quality, but not for food quality.

4.3. Quality of Service by Restaurant Tier

Having completed the main analysis, we next turn to examining how the effect of Uber and Lyft on the service quality of a restaurant depends on the tier of the restaurant. If our hypothesis is correct, one expects the impact of Uber's and Lyft's presence on service

Table 4. Difference-in-Difference (Food)

	Dependent variable: *Ratio of complaints on food*			
	(1)	(2)	(3)	(4)
Constant	0.167***			
	(0.003)			
Austin dummy	−0.007	−0.007		
	(0.005)	(0.005)		
Before Uber/Lyft exit	0.001		0.001	
	(0.003)		(0.003)	
After Uber/Lyft return	0.001		0.001	
	(0.003)		(0.003)	
Austin dummy × Before Uber/Lyft exit	−0.004	−0.003	−0.003	−0.002
	(0.006)	(0.006)	(0.006)	(0.006)
Austin dummy × After Uber/Lyft return	0.003	0.003	0.003	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Monthly fixed effect	N	Y	N	Y
Restaurant fixed effect	N	N	Y	Y
Observations	58,227	58,227	58,227	58,227
R^2	0.0002	0.001	0.060	0.061
Adjusted R^2	0.0001	0.0001	0.042	0.042

Note. Standard errors are clustered at restaurant level.
**$p < 0.05$; ***$p < 0.01$.

Table 5. Difference-in-Difference ($ Restaurant)

	Dependent variable: *Ratio of complaints on service*			
	(1)	(2)	(3)	(4)
Constant	0.111***			
	(0.008)			
Austin dummy	0.059***	0.055***		
	(0.010)	(0.011)		
Before Uber/Lyft exit	0.014		0.013	
	(0.010)		(0.009)	
After Uber/Lyft return	0.008		0.009	
	(0.009)		(0.008)	
Austin dummy × Before Uber/Lyft exit	−0.014	−0.010	−0.012	−0.007
	(0.013)	(0.014)	(0.013)	(0.013)
Austin dummy × After Uber/Lyft return	0.023	0.030**	0.018	0.025**
	(0.012)	(0.013)	(0.011)	(0.012)
Monthly fixed effect	N	Y	N	Y
Restaurant fixed effect	N	N	Y	Y
Observations	12,771	12,771	12,771	12,771
R^2	0.015	0.018	0.140	0.143
Adjusted R^2	0.015	0.013	0.120	0.119

Note. Standard errors are clustered at restaurant level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

quality to be more pronounced for restaurants whose service workers are paid less. Those workers are more likely to be lured by gig work opportunities. To formally test this idea, we divide restaurants into two tiers based on labels given by the Yelp app describing their price ranges. Our first tier consists of those restaurants that are assigned only one dollar sign in the app, meaning they are cheaper. The rest of the restaurants comprise our second tier, which can have two to three dollar signs. We conduct the same DiD analysis in Equation (1) for one dollar sign and two to three dollar signs separately. Table 5 shows the result for low-tier (cheaper), one-dollar-sign restaurants.

Similar to the previous study, for low-tier (cheaper) one-dollar-sign restaurants, β_1 is nonsignificant in all of the estimated models. More interestingly, β_2 is positive and significant. As this table shows, the return of Uber and Lyft to the city is associated with about a 2.5 percentage point increase in the difference between the likelihood that review written for a one-dollar-sign restaurant in Austin contains a complaint about service and the likelihood that the same happens with a one-dollar-sign restaurant in Dallas (in column (4) with both fixed effects). In contrast, when we run the same regression for two- to three-dollar-sign restaurants, the results are not significant as shown in Table 6. As can be seen from this table, β_2 is not significant anymore, which is expected given our hypothesis. We show that the quality of service for higher tier restaurants in Austin do not drift apart once Uber and Lyft enter Austin from those of Dallas.

This is another piece of evidence for our hypothesis regarding the mechanism through which the presence of rideshare companies in Austin affects the quality of the service in its restaurants. Our hypothesis is that service quality drops because retaining service employees is harder for low-tier restaurants when employees have gig work opportunities as attractive outside options. As such, it is reasonable to expect the effect to be stronger for one-dollar-sign restaurants whose staff are more likely to consider driving for Uber or Lyft a viable alternative to their current jobs. This is in line with the observations from Tables 5 and 6 that the effect is stronger only for low-tier restaurants and not for high-tier restaurants.

Our analysis so far presents multiple pieces of evidence that are consistent with our hypotheses. We first show the relationship between Uber's and Lyft's return to the city and the restaurant's service quality. Also, Uber's and Lyft's impact is more pronounced for cheaper restaurants whose service workers are more likely to be lured by gig work opportunities. In particular, our finding that Uber's and Lyft's return to the city affects a restaurant's service quality but not the food quality gives support for our second hypothesis that the gig economy impacts the quality of service through the labor market.[19] Nevertheless, it is indirect evidence of such a mechanism. Next, we investigate Hypothesis 2 more formally—whether employee turnover in the restaurant industry is affected in Austin by the presence of rideshare companies—to provide such direct evidence using a different data set.

5. Analysis of Staff Turnover in Restaurants

We conduct a series of analyses to provide direct evidence for our mechanism by examining the impact on

Table 6. Difference-in-Difference ($$ or $$$ Restaurant)

	Dependent variable: *Ratio of complaints on service*			
	(1)	(2)	(3)	(4)
Constant	0.169***			
	(0.003)			
Austin dummy	0.014**	0.013**		
	(0.006)	(0.006)		
Before Uber/Lyft exit	−0.003		−0.005	
	(0.003)		(0.003)	
After Uber/Lyft return	−0.003		−0.003	
	(0.003)		(0.003)	
Austin dummy × Before Uber/Lyft exit	0.011	0.011	0.011	0.012
	(0.007)	(0.007)	(0.007)	(0.007)
Austin dummy × After Uber/Lyft return	0.005	0.006	0.003	0.005
	(0.007)	(0.007)	(0.006)	(0.006)
Monthly fixed effect	N	Y	N	Y
Restaurant fixed effect	N	N	Y	Y
Observations	45,456	45,456	45,456	45,456
R^2	0.001	0.003	0.125	0.127
Adjusted R^2	0.001	0.001	0.109	0.109

Note. Standard errors are clustered at restaurant level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

staff turnover in local restaurants resulting from the return of rideshare companies (i.e., Hypothesis 2). We build parallels to those conducted using Yelp review data in Section 4.

5.1. Main Analysis

We start by examining how the turnover rate of staff in Austin's restaurants changes with the presence of rideshare companies in the city. We conduct this analysis in a DiD manner, using Dallas as the control group.

We estimate a Cox proportional hazard model for employee turnover rates in a similar manner to Clotfelter et al. (2008). Our dependent variable is hazard rate λ_{itn}, the probability that employee n quits restaurant i during calendar month t conditional on n having been working for i for $\tau - 1$ months. The Cox proportional hazard function applied to our setting can be represented as follows:

$$\lambda_{itn} = h(\tau_{itn}) \times e^{X_{itn}\beta}. \tag{3}$$

In this formulation, $h(\tau_{itn})$ is the baseline hazard rate that depends only on τ_{itn}, how long employee n has been working at restaurant i when the employee is observed in period t. The second term, $e^{X_{itn}\beta}$, is parametrically estimated, and it captures how the hazard rate is affected by the covariates X for each observation itn. In our model, $X_{itn}\beta$ is assumed to be

$$\begin{aligned} X_{itn}\beta \equiv\ & \beta_0 X^0_{itn} + \beta_1 \cdot I(\mathrm{i} \in \mathrm{Austin}) \cdot I(t \in \mathrm{Before}) \\ & + \beta_2 \cdot I(\mathrm{i} \in \mathrm{Austin}) \cdot I(\mathrm{t} \in \mathrm{After}), \end{aligned} \tag{4}$$

where X^0_{itn} includes other observable variables, such as average hourly wage, position at the restaurant, and monthly and restaurant fixed effects. Our coefficient of interest is β_2, which captures the effect of Uber's and Lyft's return to Austin on the employee turnover hazard rate relative to that in Dallas. Table 7 presents the results.

Table 7. Turnover Rate Analysis

	Dependent variable: *Turnover hazard rate*
AvgHourlyWage	−0.048***
	(0.003)
Austin dummy × Before Uber/Lyft exit	0.074
	(0.058)
Austin dummy × After Uber/Lyft return	0.115**
	(0.052)
Restaurant fixed effect	Y
Monthly fixed effect	Y
Observations	553,404
(Pseudo) R^2	0.051

Note. Standard errors are clustered at restaurant level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Similar to the previous study, β_1 is nonsignificant in all of the estimated models. More interestingly, in line with Hypothesis 2, β_2 is positive and significant. This roughly means that the presence of Uber and Lyft in Austin increases the hazard rate that a given restaurant worker quits in a given month by about 11.5% (note that this is percentage and not percentage point).

To get a sense of the magnitude of this effect in dollar terms, one can compare the estimated $\beta_2 = 0.115$ to the estimated effect of hourly wage on hazard rate ($\beta_0^{wage} = -0.048$). From Table 7, one can calculate that the effect of Uber's and Lyft's return to Austin is equivalent to that of a uniform \$2.40 decrease in hourly wages (i.e., $\beta_2/\beta_0^{wage} = -2.40$). This amounts to about 20% of the average hourly wage paid to the employees in our Austin data (average hourly wage = \$11.8 from Table 2). It suggests that restaurants in Austin increase, on average, 20% their wages to successfully combat the new threat from the gig economy and retain current workers for customer service satisfaction management.

To summarize, we show that the turnover rate of staff increases in Austin relative to Dallas once Uber and Lyft return to the city. This is consistent with the main finding in Section 4 that the service quality deteriorates after the comeback of Uber and Lyft.

5.2. Employee Turnover Moderated by Job Position

Next, we perform an analysis in a parallel manner to our analysis of food- and service-related reviews in Section 4.2. We show the impact of the presence of Uber and Lyft is mainly on service quality rather than food quality, likely a result of the fact that service workers are more likely to switch to gig work than chefs. Here, we conduct a similar analysis in the employee-turnover space.

Formally, we compare the patterns of turnover between two different positions in restaurants. We expect the effect of Uber's and Lyft's return to the Austin market to be larger for those workers who tend to provide the service (front-of-house employees) compared with those workers who are involved in preparing the food such as chefs (back-of-house employees).[20] We conduct two separate DiD analyses for these two groups and demonstrate that the results from the turnover data are consistent with the results from the Yelp data. Table 8 presents the results.

As can be seen from Table 8, the coefficient of interest *Austin dummy* × *After Uber/Lyft return* is positive and significant for front-of-house workers ($\beta_2 = 0.163$) but nonsignificant for back-of-house workers. This is similar to the results from Yelp data showing that the effect of Uber's and Lyft's presence is significant on service quality only and not food quality.

The current results can be also interpreted from the long-term career opportunity (e.g., David and Houseman 2010). The impact of Uber/Lyft on turnover rates were significantly different between BOH and FOH even after controlling for wage. In general, low-level kitchen workers may eventually become high-level chefs by learning skills in the long run, but waiters may not expect a long-term, future career prospect, which makes them more vulnerable to the presence of Uber and Lyft.[21]

5.3. Employee Turnover by Restaurant Category

In this section, we conduct an analysis parallel to our tier-based analysis of Yelp reviews in Section 4.3. In employee turnover data, we do not observe the price tier of the restaurants, such as the dollar sign in Yelp data. Instead, we can observe to which of the following categories each restaurant belongs: quick service, fast casual, casual dining, upscale casual, and fine dining. This categorization approximately resembles the price-tier of the restaurants. Similar to the analysis using a dollar sign in Yelp, we split the sample by the restaurant category into two broad groups: a low-tier

Table 8. Turnover Rate by Worker Job Position

	Dependent variable: *Turnover hazard rate*	
	Front-of-house workers	Back-of-house workers
AvgHourlyWage	−0.042***	−0.109***
	(0.003)	(0.005)
Austin dummy × *Before Uber/Lyft exit*	0.037	0.108
	(0.070)	(0.065)
Austin dummy × *After Uber/Lyft return*	0.163**	0.079
	(0.073)	(0.050)
Restaurant fixed effect	Y	Y
Monthly fixed effect	Y	Y
Observations	274,180	279,224
(Pseudo) R^2	0.047	0.064

Note. Standard errors are clustered at restaurant level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 9. Turnover Rate by Restaurant Tier

	Dependent variable: *Turnover hazard rate*	
	Low-tier (quick service, fast casual)	High-tier (casual dining, upscale casual, fine dining)
AvgHourlyWage	−0.060***	−0.048***
	(0.010)	(0.003)
Austin dummy × *Before Uber/Lyft exit*	0.168**	0.030
	(0.079)	(0.069)
Austin dummy × *After Uber/Lyft return*	0.264***	0.052
	(0.101)	(0.055)
Restaurant fixed effect	Y	Y
Monthly fixed effect	Y	Y
Observations	128,676	424,728
(Pseudo) R^2	0.065	0.050

Note. Standard errors are clustered at restaurant level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

restaurant group for quick service and fast casual[22] and a high-tier restaurant group for casual dining, upscale casual, and fine dining. We investigate which restaurant group is more affected. We repeat our main analysis of the employee turnover data for each category. Table 9 presents the results.

The results from Table 9 are again consistent with findings from our Yelp reviews analysis. As can be seen from this table, the coefficient *Austin dummy* × *After Uber/Lyft return* is positive and significant for quick service and fast casual restaurant but not for others. We interpret this in a similar way to how we interpret the results from a tier-based analysis of reviews in Tables 5 and 6. It shows a consistent pattern that the turnover rate in low-tier restaurants (quick service and fast casual) gets higher than relatively high-end restaurants (casual dining, upscale casual and fine dining) after Uber and Lyft return to the city. Thus, the impact of Uber's and Lyft's presence on service quality is more pronounced for restaurants whose service workers are paid less.[23]

6. Robustness Checks and Alternative Explanations

6.1. Overview of Robustness Checks

We conduct a series of robustness checks for our analysis of Yelp reviews and employee turnover data. In this section, we overview a series of those robustness checks, the details of which are relegated to the online appendix. We carry out the following robustness analyses:

1. "Placebo" treatment timing: We run our main DiD regression specification with a small twist. We replace the entry time of Uber and Lyft (which was May 2017) with May 2018. We expect the effect of this placebo treatment to be statistically nonsignificant. The regression results (presented in detail in the online appendix) confirm this expectation for both the reviews and employee turnover data. This validates that the observed change in service quality during the time period marked by the return of Uber and Lyft (i.e., May 2017–May 2019 in our data) is not from other forces during the same period.

2. Changing the control topic: In our analysis of Yelp reviews, some of our regressions use food quality as another dependent variable (recall that service quality was the target dependent variable). Our main channel for the effect of the gig economy on the restaurant is through the labor market. If our hypotheses are correct, we expect no impact of Uber's and Lyft's presence on a restaurant's ambiance. We check whether our results are robust to that choice by replacing it with other topics (such as ambiance). The results remain robust.

3. Keyword selection for each topic: In this robustness analysis, we change the dictionaries and try a broader set of keywords to decide whether a sentence in a review is related to food or service. We rerun the analysis in order to see if the estimation results are sensitive to this change. The results remain robust.

4. Alternative measurements of service/food quality from reviews: We repeat our main analysis of service and food quality using alternative measurements of the dependent variable. First, we change the aggregation level. We further aggregate reviews up to the restaurant-year level instead of the restaurant-month level. We also further disaggregate to the individual review level instead of restaurant-month. In both cases, the results are robust. Second, we use the absolute number of negative reviews instead of relative ones. The results are still mostly robust. Finally, we modify the dependent variable in order to give a larger weight to reviews that are longer and more detailed. Again, the results are robust.

5. Changing the control city: Our regressions use Dallas restaurants as a control group (recall that Austin was the treatment group). We check whether our

results are robust to that choice by replacing it with San Antonio. We perform two analyses. First, we change the control city from Dallas to San Antonio. The DiD results are still significant. Second, we change the treatment city from Austin to San Antonio (holding Dallas as a control city). The DiD coefficient becomes nonsignificant. We do this for both the reviews and the employee turnover data. The results remain robust. This validates that our results are not artifacts from the characteristics of a specific control group.

6. Parallel trends analysis: Next, we also check the validity of our control by analyzing the review data at the yearly and quarterly levels and confirm that, indeed, prior to the exit of Uber and Lyft from Austin, the trends of review sentiments about service are parallel between Austin (treatment city) and Dallas (control city).

7. Quality versus quantity of workers and the interpretation of the underlying mechanism: Higher employee turnover may reduce the service quality of a restaurant in two ways: (i) by reducing the number of restaurant workers or (ii) by reducing "worker quality." Here, we delve into our mechanism further to see the effect of these two channels. We first change the dependent variable in the analysis of our employee data. In particular, we use the number of workers at each restaurant in each month as a dependent variable. DiD analysis shows that Uber's and Lyft's presence in the city of Austin has a negative impact on this variable as well. As for worker quality, we study the change in a worker hazard rate to examine the impact of ridesharing companies on worker experience using a tenure period of each worker as a dependent variable. The result indicates that worker tenure gets shorter so that workers have less chance to accrue experience related to restaurant quality. Thus, in addition to our main hypothesis (i.e., Uber and Lyft reduce service quality through impacting turnover), Uber and Lyft may reduce the service quality through both worker quality and worker quantity, at least in the short run.

8. Short- versus long-term effects: We carry out further analysis to see whether the impact of Uber and Lyft on the labor market is more a short- or long-run effect. We examine the effect on employee turnover, worker size, and average hourly wage. We first find that effect on turnover is reasonably long run but is attenuated over time. The result further reveals that the worker quantity impact of Uber's and Lyft's presence in the market is weaker in the second year after their return compared with the first year. We also show that restaurant worker wages in Austin increase more than they do in Dallas in the second year after Uber and Lyft return to Austin. Given that we have only two years of data, it is difficult to conclude whether the effect is more like a short- or a long-term one. But one consistent interpretation is that, when the employee turnover is high, not only does the quantity of the workforce decrease in the short term, but the average worker has less experience at any given point in time even in the long run. This is because the market correction through wage seems insufficient.[24] The effects of Uber and Lyft persist and are not driven away by the wage correction although it may alleviate over time.

9. Direct relationship between turnover and Yelp reviews: The mechanism we propose is one that works through employee turnover rates. As a result, it is worth carrying out a direct analysis studying how employee turnover and service quality comove. We conduct this analysis and show that, as expected, higher turnover is associated with a higher percentage of negative reviews about service on Yelp. One should note, however, that, reassuring as it may be, this analysis should not be interpreted causally given that there is no guarantee that the variation in turnover is exogenous. Such causality concerns are indeed part of the reason why, in our main analysis, we turn to a natural experiment.

6.2. Alternative Demand-Side Explanations

Our analyses so far present evidence for the impact of Uber and Lyft on restaurants' service quality through the labor market (employee turnover). However, in principle, it is conceivable that the return of these two rideshare companies to Austin led to changes in the reviews through channels other than employee turnover. In particular, the presence of Uber and Lyft may have consequences for demand for restaurants, which can, in turn, impact service quality. The potential impact of the gig economy on other parts of the economy through demand-side channels is documented before (e.g., Zhang et al. 2022). As such, in this section, we perform some analyses to study whether Uber's and Lyft's return to Austin may impact reviews through a demand-side channel. In particular, we focus on two possible demand-side hypotheses.

First, Uber and Lyft make transportation easier, thereby allowing customers to experience more restaurants, which may, in turn, raise their standards and lead to harsher reviews. We can first easily check whether the number of reviews changes after Uber and Lyft returned to Austin, contributing to the observed pattern. The average monthly number of reviews per restaurant was 5.85 when they were absent and 5.68 when they returned ($p = 0.143$). Also, the percentage of reviews on service were 54.6% and 54.5%, respectively ($p = 0.839$), and the percentage of reviews on food were 67.3% and 67.9%, respectively ($p = 0.281$). Thus, we do not find evidence that those companies' returns might have increased the number of restaurant visits and reviews over time.

More importantly, we believe the preceding hypothesis does not explain some of the evidence we have already presented in the paper. First, Tables 5

Table 10. Median Distance Between Home and Restaurants

	Dependent variable: *log(distance from home)*
Austin dummy × After Uber/Lyft return	0.006
	(0.008)
Restaurant fixed effect	Y
Monthly fixed effect	Y
Observations	35,323
R^2	0.673
Adjusted R^2	0.628

Note. Standard errors are clustered at restaurant level.

and 6 show that the impact of Uber's and Lyft's presence on perceived service qualities of restaurants is significant only for one-dollar-sign restaurants and not for others. Second, a comparison between Tables 3 and 4 suggests the impact of Uber and Lyft on negative reviews about food quality is, unlike service quality, nonsignificant. As we discuss before, both of these heterogeneity patterns are quite in line with our supply-side hypothesis. But, in order for the aforementioned demand-side explanation to be congruent with these patterns, it has to be that the presence of Uber and Lyft raised customer expectations only for one-dollar-sign restaurants and only for service rather than for food or ambiance. Though in principle feasible, this scenario is substantially more convoluted than our supply-side theory supported by our analysis of the employee turnover data.

A second possible demand-side explanation for the impact of Uber and Lyft on restaurants' service quality is one based on selection: Uber and Lyft make transportation easier, potentially enabling harsher reviewers to visit more restaurants and leave more reviews. There are two types of evidence against this hypothesis. The first type is similar to what we mention: it is not clear why the presence of Uber and Lyft in the city of Austin should lead to more restaurant visits by customers who are more negative about service but not food. Similarly, it is not clear why the presence of these rideshare companies would lead to more restaurant visits by negative customers who eat at one-dollar-sign restaurants but not other restaurants. In sum, although selection could, in principle, be an important issue, it does not fully explain the observed heterogeneity patterns of the effect of rideshare companies on reviews observed in our data.

There is also a second type of evidence against the aforementioned selection-based, demand-side mechanism. We provide a simple analysis that shows the effect of these rideshare platforms on the reach of travel is neither substantial nor statistically significant. To this end, we use data from SafeGraph, a firm collecting and providing retail traffic data. SafeGraph data provides the median traveling distance of customers between their home and each restaurant. It is a one-year-period of panel data at the restaurant-month level starting from January 2017. We have observations in only two cities, Austin and San Antonio, in this data, so we compare two cities in this analysis.[25]

Using data from SafeGraph, we run a regression similar to our main DiD analysis in Equation (1) but with a different dependent variable. Instead of our measure of service quality, we use the logarithm of the median distance traveled by customers to restaurants in Austin and San Antonio for 12 months between January 2017 and January 2018.[26] As Table 10 shows, the effect is small in magnitude and statistically nonsignificant. It suggests that there is little evidence that rideshare companies significantly change the travel distance of restaurant guests, which mitigates the selection concerns because customers do not seem to change their travel pattern after Uber and Lyft returned.

To sum up, although we cannot completely rule out all of these alternative accounts, they cannot fully explain the patterns observed in our data. The evidence we present in our analysis suggests the negative effect of Uber's and Lyft's presence on the service quality of some restaurant types arises mainly from supply-side forces rather than demand-side ones.

7. Conclusion

The rapid growth of the gig economy in recent years has transformed many sectors of the economy. Airbnb has challenged the hotel industry; Uber and Lyft have challenged traditional taxi companies and curtailed ridership on public transportation. And, whereas these effects of gig work on direct competitors is very important, more indirect effects also merit attention.

In this paper, we examine the impacts of the gig economy on product quality in the seemingly unrelated local industries through the labor market—specifically the relationship between Uber/Lyft and restaurant quality. We hypothesize that Uber's and Lyft's presence in a city lowers the quality of the local restaurants' waitstaff by increasing turnover, thereby adversely impacting the quality of service they can offer. To test our hypotheses, we exploit a natural experiment in which, because regulatory changes, Uber and Lyft exited the market in Austin, Texas, in

May 2016 and returned in May 2017. We apply text analysis to Yelp reviews from 2014 to 2019 and use a difference-in-difference approach to determine whether the entry and exit of Uber and Lyft influenced customer satisfaction with local restaurants. Dallas serves as a control group.

We find that the entry of rideshare companies corresponds to a reduction in customer satisfaction with service quality at local restaurants. We explain this effect through the labor force: the presence of a gig economy provides an attractive employment option that draws people away from low-wage, low-skill work in restaurants. This reduced labor pool for restaurants, in turn, affects service quality. We reinforce this interpretation with several other analyses. First, we demonstrate that customer satisfaction with food quality as opposed to service quality remains unaffected by the entrance and exit of Uber and Lyft. This falls in line with our hypothesis given that back-of-house positions (e.g., chef, manager) are desirable enough that driving for Uber and Lyft is not an attractive alternative. Second, we find that the effect is especially pronounced at less expensive restaurants, signified by a single dollar sign in Yelp, compared with restaurants with a label of two or three dollar signs; we assume that service workers at less expensive restaurants are more likely to be lured away by gig work opportunities. Finally, we examine turnover rates of staff in restaurants by leveraging a unique worker-level data set of restaurants in Austin and Dallas from 2014 to 2019. Turnover rates increase in Austin relative to Dallas once Uber and Lyft return. The magnitude of this effect is estimated at about 20% of the average hourly wage paid to the employees in our Austin data. Importantly, this increase is confined to low-end restaurants (quick service and fast casual) and unobserved in middle- or high-end restaurants; likewise, it is observed only for front-of-house workers, whereas there is no effect on back-of-house staff.

Our paper contributes to marketing literature, especially in the area of service marketing and the role of the employee for customer satisfaction, making a connection between employee turnover and customer satisfaction about a restaurant's service quality. These results present compelling evidence that gig work, in this case employment with Uber and Lyft, have ramifications that extend far beyond industries in direct competition with rideshare companies. As the gig economy expands, as it is predicted to do, understanding these second order effects will be critical for the development of effective regulatory policy. Our work focuses on the hospitality sector, but we consider it a telling case study for the economy as a whole and hope it serves as a starting point for deeper study of how gig work may shape the future economy.

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Endnotes

[1] "Uber Competing with Restaurants for Workers" (April 29, 2018): https://ride.guru/content/newsroom/uber-competing-with-restaurants-for-workers.

[2] *The Nation's Restaurant News*, for example, reported that two thirds of restaurant owners cite the difficulty of hiring workers who can provide sales service as their top concern (August 30, 2018): https://www.nrn.com/workforce/operators-grapple-tight-labor-market.

[3] Katz and Krueger (2019, p. 2) define such alternative work arrangements as "temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers."

[4] The Bureau of Labor Statistics in 2019 projected 14% growth in job opportunities for "food and beverage serving and related workers" during the next 10 years. (https://www.bls.gov/ooh/food-preparation-and-serving/food-and-beverage-serving-and-related-workers.htm).

[5] See https://www.bls.gov/careeroutlook/2016/article/what-is-the-gig-economy.htm.

[6] "One reason for the shortage of restaurant workers? Driving for Uber comes with better perks," ML.com (May 10, 2018): https://www.mic.com/articles/189312/one-reason-for-the-shortage-of-restaurant-workers-driving-for-uber-comes-with-better-perks.

[7] In the People Report (2017) by Blackbox Intelligence (formerly, TDn2K), a consulting company specializing in the restaurant industry, it is shown that service staffs of front-of-house workers have a turnover of 154%, whereas management turnover ranges between 40% and 50%: https://www.nrn.com/operations/4-big-challenges-restaurants-right-now.

[8] Another important point of difference is the natural experiment we leverage. Compared with other approaches using endogenous entry (e.g., Burtch et al. 2018, Barrios et al. 2022, Gorback 2020), such as examining cities that rideshare entered earlier, our approach utilizes exogenous shocks for our identification strategy. A notable exception is Zhang et al. (2022) who also leverage an exogenous shock in the same natural experimental setting as ours and provide a clean identification.

[9] Uber and Lyft arrived in Austin, Texas, in the spring of 2014. In December of the following year, the city council passed an ordinance requiring fingerprint background checks for all rideshare drivers. Uber and Lyft refused to take fingerprint background checks and fought back. Austin ultimately prevailed, and unwilling to concede the demand, Uber and Lyft canceled service in May of 2016. Both companies went up to the state level, where they lobbied aggressively for House Bill 100, "relating to the regulation of transportation network companies." The bill passed and, among other things, scuttled requirements statewide for fingerprint background

checks of rideshare employees. In May of 2017, Uber and Lyft were back in Austin.

[10] We analyze further to discuss these two channels in Online Appendix A-8, in which we find that higher employee turnover reduces the service quality through both worker quantity and quality.

[11] Schneider and Bowen (1993) report that high employee turnover implies the loss of experienced employees and established customer relationships, resulting in negative effects on customer satisfaction. Thus, the effect of the second shock may be immediate, whereas the effect of the first shock may not because the knowledge accumulation take longer time. We thank an anonymous reviewer for suggesting this point for us.

[12] Review texts are the best available source for eliciting attribute-level performance proxies for restaurants, and attribute-level sentiments in reviews are shown to be of significant economic value to businesses (Wu et al. 2015).

[13] Jed Kolko, a chief economist at Indeed.com, analyzed job postings and socioeconomic factors across different cities and selected Dallas as the most similar city to Austin, followed by Atlanta, Denver, Phoenix, and San Antonio (https://www.nytimes.com/interactive/2018/04/03/upshot/what-is-your-citys-twin.html).

[14] We apply several different selection rules to exclude small restaurants. Our main results are robust to other thresholds such as 50 (average one review per month) or 300 (average five reviews per month).

[15] For more details on lexicon-based methods for sentiment analysis, see Taboada et al. (2011).

[16] It does not include tipped income of workers. So we cannot back up our analysis using dollar sign of restaurants directly. Also, we do not know individual work hours or work shifts. The wage is coded as average hourly wage in their work shift.

[17] The categorization in this data set is performed by the data collection company, which does not necessarily coincide with Yelp's three-tier categorization of $, $$, and $$$.

[18] In every kitchen, there are a number of different job roles that keep a kitchen running smoothly. Some are highly paid for their culinary expertise and performing other roles, such as overseeing and training personnel, planning menus, managing the culinary budget, and sometimes purchasing. Executive chefs, head chefs, and sous chefs belong to this category. However, others such as kitchen porters are not well paid. This person is in charge of simple tasks involved in the basic preparations of the food. Nevertheless, obtaining such experience can expand worker's future career opportunities to become a chef in the future. This long-term career opportunity (David and Houseman 2010) is an important factor here.

[19] There can be a concern that the price is a confounding variable. First, we note that a good indicator of a restaurant's price level is its Yelp-assigned tier based on the number of dollar signs. To the best of our knowledge, each restaurant's Yelp tier remained by and large constant in our data set. We checked the stability of the restaurant dollar sign in Yelp by studying the historical snapshot of Yelp data sets. We indeed found 99.96% of dollar signs remain constant between November 2018 and January 2021. Therefore, a price confound has to be more of a between-restaurant issue (i.e., a higher portion of expensive restaurants opening up in Austin) rather than a within-restaurant one (i.e., a higher portion of Austin's existing restaurants moving up to more expensive tiers). With this in mind, we did our analysis controlling for this between-restaurant issue in two ways: (i) we only work with restaurants that were there for the entirety of our time period (see our discussion in Endnote 13). (ii) More importantly, we use restaurant fixed effects in our analysis. As a result, we do not expect prices to confound our analysis. Moreover, we believe that, if our results were an artifact of a price confound (e.g., "given this high price, food is not good" or "given this price, the service is not good"), we would have expected to find them across the board for both food and service. However, as we show in our analysis in Section 4.2, it is not the case and, thus, renders support for our mechanism.

[20] FOH and BOH are widely used industry terms in restaurant and beverage industries (https://www.restaurantinformer.com/2012/07/foh-boh-what-to-know/).

[21] We thank an anonymous reviewer for pointing out this angle for us.

[22] There are only 21 and 3 restaurants belonging to the quick service category in Austin and Dallas, respectively, in our turnover data (note that there are 103 and 67 restaurants in fast casual categories in Austin and Dallas; see Table 2). For these reasons, we combine quick service and fast casual together in one category for the low-tier group in the revised manuscript. The results are robust to whether to include the quick service category. This ensures that our results are not driven by the quick service restaurant category.

[23] A high employee turnover rate can imply higher mobility of service workers switching between restaurants. Thus, one may consider potential spillover such that more high-wage workers have switched to Uber and Lyft, and as a result, high-tier restaurants hire workers from low-tier restaurants. This spillover effect could have driven the result. To test this alternative possibility, we analyzed the workforce migration (switching) patterns in our data set. In our data set, we have a total of 150,000 workers. We observed about 8% of workers (i.e., about 12,000 workers) changed their jobs (restaurants) at least once (i.e., workers quit at one restaurant and later worked for another restaurant in our data set). We calculate the conditional probability of job switching between different restaurant tiers in our data set. Most workers who changed their jobs switched restaurants only within the same tier (97.2% and 98.5% for low- and high-tier, respectively). Only 2.8% of job switchers moved up to a high-tier restaurant, suggesting that such spillover is extremely rare and unlikely to drive our results.

[24] The differential wage increase between Austin and Dallas is about 40 cents/hour, nearly five times smaller than our estimate of the amount by which Uber's and Lyft's presence makes restaurant jobs less desirable. See the online appendix for the details.

[25] SafeGraph confirmed that they disposed of observations before 2018. We obtained the observations between 2017 and 2018 for the two cities (Austin and San Antonio) before they disposed of those data points. Unfortunately, we could not obtain Dallas restaurant data to directly conduct a similar DiD as we did in our main analysis. Instead, we use San Antonio as an alternative control city here. As the robustness check shows in Online Appendix A-5, our results are still significant when we change the control city from Dallas to San Antonio.

[26] In addition to the change in dependent variable, there is another, small difference. We exclude the interaction term between *Austin dummy* and *Before Uber/Lyft exit dummy* because the time span of the SafeGraph data starts after Uber's and Lyft's exit in 2016.

References

Barrios JM, Hochberg YV, Yi H (2022) Launching with a parachute: The gig economy and new business formation. *J. Financial Econom.* 144(1):22–43.

Barrios T, Diamond R, Imbens GW, Kolesár M (2012) Clustering, spatial correlations, and randomization inference. *J. Amer. Statist. Assoc.* 107(498):578–591.

Barron K, Kung E, Proserpio D (2021) The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Sci.* 40(1):23–47.

Berger J, Sorensen AT, Rasmussen SJ (2010) Positive effects of negative publicity: When negative reviews increase sales. *Marketing Sci.* 29(5):815–827.

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

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *Quart. J. Econom.* 119(1):249–275.

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

Chakraborty I, Kim M, Sudhir K (2022) Attribute sentiment scoring with online text reviews: Accounting for language structure and missing attributes. *J. Marketing Res.* 59(3):600–622.

Chen MK, Rossi PE, Chevalier JA, Oehlsen E (2019) The value of flexible work: Evidence from Uber drivers. *J. Political Econom.* 127(6):2735–2794.

Clotfelter C, Glennie E, Ladd H, Vigdor J (2008) Would higher salaries keep teachers in high-poverty schools? Evidence from a policy intervention in North Carolina. *J. Public Econom.* 92(5–6): 1352–1370.

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

David H, Houseman SN (2010) Do temporary-help jobs improve labor market outcomes for low-skilled workers? Evidence from work first. *Amer. Econom. J. Appl. Econom.* 2(3):96–128.

Di X, Fabusuyi T, Simek C, Chen X, Hampshire R (2019) Inferred switching behavior in response to re-entry of Uber and Lyft: A revealed study in Austin, Texas. *Findings*, 7568.

Estelami H (2000) Competitive and procedural determinants of delight and disappointment in consumer complaint outcomes. *J. Service Res.* 2(3):285–300.

Farronato C, Zervas G (2019) Consumer reviews and regulation: Evidence from NYC restaurants. Working paper, Harvard Business School, Cambridge, MA.

Glaeser EL, Kim H, Luca M (2018) Nowcasting gentrification: Using Yelp data to quantify neighborhood change. *AEA Papers Proc.* 108:77–82.

Gorback C (2020) Your Uber has arrived: Ridesharing and the redistribution of economic activity. Working paper, University of Texas at Austin, Austin, TX.

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

Hancock JI, Allen DG, Bosco FA, McDaniel KR, Pierce CA (2013) Meta-analytic review of employee turnover as a predictor of firm performance. *J. Management* 39(3):573–603.

Holtom BC, Burch TC (2016) A model of turnover-based disruption in customer services. *Human Resources Management Rev.* 26(1): 25–36.

Hurley RF (2002) Putting people back into organizational learning. *J. Bus. Indust. Marketing* 17(4):270–281.

Jackson E (2020) Availability of the gig economy and long run labor supply effects for the unemployed. Working paper, Michigan State University, East Lansing, MI.

Jefferson-Jones J (2015) Can short-term rental arrangements increase home values? A case for Airbnb and other home sharing arrangements. *Cornell Real Estate Rev.* 13:12–19.

Katz LF, Krueger AB (2017) The role of unemployment in the rise in alternative work arrangements. *Amer. Econom. Rev.* 107(5):388–392.

Katz LF, Krueger AB (2019) The rise and nature of alternative work arrangements in the United States, 1995–2015. *Indust. Labor Relations Rev.* 72(2):382–416.

Kim DH (1993) The link between individual and organizational learning. *Sloan Management Rev.* 35(1):37–51.

Koys DJ (2001) The effects of employee satisfaction, organizational citizenship behavior, and turnover on organizational effectiveness: A unit-level, longitudinal study. *Personnel Psych.* 54(1): 101–114.

Lee J, Jin J, Luca M (2018) Aggregation of consumer ratings: An application to Yelp.com. *Quant. Marketing Econom.* 16(3):289–339.

Sasser WE, Schlesinger LA, Heskett JL (1997) *Service Profit Chain* (Simon and Schuster, New York).

Schneider B, Bowen DE (1993) The service organization: Human resources management is crucial. *Organ. Dynamics* 21(4): 39–52.

Shin J (2005) The role of selling costs in signaling price image. *J. Marketing Res.* 42(3):302–312.

Taboada M, Brooke J, Tofiloski M, Voll K, Stede M (2011) Lexicon-based methods for sentiment analysis. *Comput. Linguistics* 37(2): 267–307.

Taddy M (2013) Multinomial inverse regression for text analysis. *J. Amer. Statist. Assoc.* 108(503):755–770.

Wu C, Che H, Chan TY, Lu X (2015) The economic value of online reviews. *Marketing Sci.* 34(5):739–754.

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

Zhang S, Lee D, Singh PV, Mukhopadhyay T (2022) Demand interactions in sharing economies: Evidence from a natural experiment involving airbnb and uber/lyft. *J. Marketing Res.* 59(2): 374–391.