The Impact of Gig Economy on the Product Quality through the Labor Market: Evidence from Ride-sharing 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 re-entry of rideshare platforms, Uber and Lyft into the city due to 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 to 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 to 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.

Keywords: Gig economy, labor market, Uber/Lyft, restaurant quality, Yelp review, Diff-in-Diff, text analysis, employee turnover rate

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1 Introduction

How does restaurant quality change when Uber and Lyft, new rideshare companies, enter the market? The gig economy has significantly transformed the landscape of several industries. For instance, rideshares like Uber and Lyft have altered the way people use public transportation and taxis. Airbnb has challenged existing hotel chains and 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 ride-sharing companies operate?

One would naturally expect, if there were a relationship, the main channel for the impact of rideshares like Uber and Lyft on the local restaurant to be through the mobilization of demand. In this paper, however, we investigate a different mechanism.: labor quality. Uber and Lyft's presence in a city may take away labor from people who would have otherwise chosen to work in a restaurant.[1] Despite the large number of people currently employed in 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-skilled workers. Katz and Krueger (2019) find that these types of work arrangements rose from 10.1 percent in February 2005 to 15.8 percent 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 U.S.[4] speaks to its significance.

While 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 U.S., accounting for approximately 34 percent of the workforce, are "gig workers." This figure is projected to increase to 43 percent in 2020.[5] This opens a significant new opportunity for low-skilled laborers. The

[1] "Uber Competing with Restaurants for Workers," (Apr 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 as their top concern (*Nation's Restaurant News*, August 30, 2018): https://www.nrn.com/workforce/operators-grapple-tight-labor-market

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

[4] The Bureau of Labor Statistics 2019 projects a 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] https://www.bls.gov/careeroutlook/2016/article/what-is-the-gig-economy.htm

labor economics literature has studied this phenomenon that workers with low pay and/or inflexible schedules are "poached" by Uber and Lyft (Chen et al., 2019; Hall and Krueger, 2018; Katz and Krueger, 2017; Huang et al., 2020); 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 where, due to 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 ride-sharing 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 setting (DiD henceforth), 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 would be 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 wait-staff 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 re-entry to Austin.

[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 People Report(2017) by Blackbox Intelligence (formerly, TDn2K), a consulting company specialized in restaurant industry shows that service staffs of front-of-house workers have a turnover of 154 percent while management turnover ranges between 40 and 50 percent: https://www.nrn.com/operations/4-big-challenges-restaurants-right-now.

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 would be paid less, either because 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 a single dollar sign restaurants whose service workers are more likely to be lured by gig-work opportunities. 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 in restaurants by leveraging a unique worker-level dataset of restaurants in Austin and Dallas from 2014-2019. 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 of staff 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 dataset to examine whether we see a similar pattern in the turnover rates for different restaurant categories. If our hypothesis is correct, we would 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-end or high-end restaurants.

We then delve deeper into the analysis by decomposing the turnover rates into turnover rates for "back-of-house" staff and "front-of-house" 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, while there is no 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 would expect some other channels through which the rideshare companies could have impacted the local economy, such as the demand changes due to the easier mobilization. While 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.

While 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-skilled workers, has far-reaching and significant ramifications on broader industries through the labor market.

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 which have documented the impacts of the gig economy on the directly related industries. Barron et al. (2018) 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 due to efficient matching technology and flexibility benefit. 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 has begun to investigate 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 has changed demand for public transportation (Di et al., 2017; Hampshire et al., 2018), demand for lodging (Zhang et al., 2018) and housing properties (Gorback, 2020), or

alchohol consumption and driving behavior (Burgdorf et al., 2019; Greenwood and Wattal, 2017). In addition to rideshare companies, researchers have investigated the impacts of other forms of the gig economy, such as examining how Airbnb affected 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 has studied 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; Huang et al., 2020). Burtch et al. (2018) and Barrios et al. (2020) examine the impact of the gig economy on the launch of new businesses and startups. The results are mixed and depend on the types of entrepreneurs. Burtch et al. (2018) show that the entry of Uber decreases the number of crowdfunding campaigns launched at Kickstarter and the number of self-employed workers, suggesting that the gig economy serves as a stable employment option for the unemployed. In contrast, Barrios et al. (2020) find that the entry of rideshare companies increases the number of new business formation in a local economy. Thus, the gig economy plays an important role in spurring entrepreneurial activity by serving as insurance in the form of an income fallback in the event of failure. Overall, these papers suggest that the gig economy may positively affect the launch of new business activities by encouraging entrepreneurs to take more risks. Still, the gig economy also offers a steady employment opportunity for the unemployed, who otherwise would have opted into new businesses.

Our paper is in line with these studies in that we also investigate the supply-side effects of the gig economy. However, these studies have not examined how the labor-market consequences of the gig economy in turn shape the performance of the impacted firms. In particular, an important but overlooked question is how the presence of gig economy in a city can impact the quality of the products/services offered by local firms. This is the gap we aim to bridge in this paper.[8] More specifically, the extant literature focuses on the impact on the relevant service categories

[8] Another important point of difference is the natural experiment we leverage. Compared to other approaches using *endogenous* entry (e.g., Gorback 2020, Burtch et al. 2018, Barrios et al. 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. (2018) that also leverage an exogenous shock in the same natural experimental setting as ours, and provides a clean identification.

through direct competition (e.g., Barron et al. 2021, investigating Airbnb's influences on housing prices and rents). On the other hand, this study shows that the ride-share 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 ridesharing companies is significant on the perceived *quality of service* but not on that of *food*.

Also, our work builds on previous literature that has focused on the causal relationship between customer satisfaction and profitability, which has been a topic of growing academic and managerial interest (Estelami 2000, Oliver 1997, Sasser et al. 1997). Several studies show a strong relationship between employee turnover and firm performance metrics such as sales and profits (Hancock et al., 2013; Call et al., 2015; Holtom and Burch, 2016), and demonstrate how employee turnover can lead to lower customer satisfaction (Hurley and Estelami, 2007; Koys, 2001). This stream of research has helped conceptualize the consequences of employee turnover on customer satisfaction and firm profit, connecting knowledge residing within employees and organizational performance (Hurley 2002, Kim 1998). For example, Schneider and Bowen (1993) report that higher levels of employee turnover can lead to lower levels of customer satisfaction in the retail store. 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-analyzing customer reviews data (Chen et al., 2014; Kuang, 2017; Glaeser et al., 2018; Humphreys and Matti, 2018; Lee et al., 2018). Some recent papers in business strategy and marketing such as Taddy (2015); Chakraborty et al. (2019); Farronato and Zervas (2019) have examined 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.

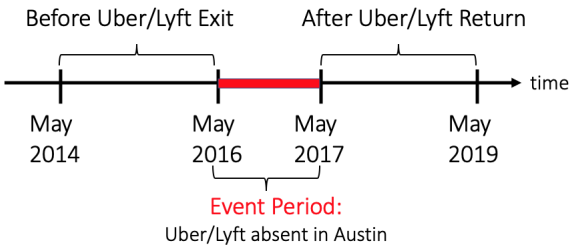


Figure 1: Timeline of a Natural Experiment in Austin

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

Figure 1 describes the timeline of Uber 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. In 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 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 due to some factors. Though we do not take a firm stance on what those mitigating factors may have been, we point out the following several possibilities.

First, we want to 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*), or

[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 cancelled 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.

(ii) by reducing the workforce *quality*. Higher turnover can imply a lack of adequate experience or training for average worker, which would eventually decrease 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 while the effect of Uber/Lyft exit, which may lead to increase in restaurant servers, may be gradual due to the learning curve.[11]

Second, it could be that the size of the second shock to the market might have been substantially larger than the first one. Hall and Krueger (2018) documented the exponential growth pattern in the number of Uber drivers in the United States from mid-2012. These patterns were consistently observed in most U.S. cities in their studies (e.g., Fig. 3 on page 15 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 to May 2016, which might have caused 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 the traditional jobs. Flexible gig work experience such as driving Uber or Lyft might have changed workers' job preference. Thus, those workers may not necessarily go back to traditional workplace such as restaurants even after Uber and Lyft left the city. They might search for other jobs that are more flexible.

Based on the above, 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 and Lyft's presence in Austin reduced the service quality of restaurants through an impact on the employee turnover in those restaurants. This translates to two main hypotheses to test.

Hypothesis 1 *(H_1) Uber and Lyft's presence in Austin led to a decrease in the service quality provided by those restaurants.*

Hypothesis 2 *(H_2) Uber and Lyft's presence in Austin led to an increase in the employee turnover for the city's restaurants.*

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

[11] We thank an anonymous reviewer for suggesting this point for us.

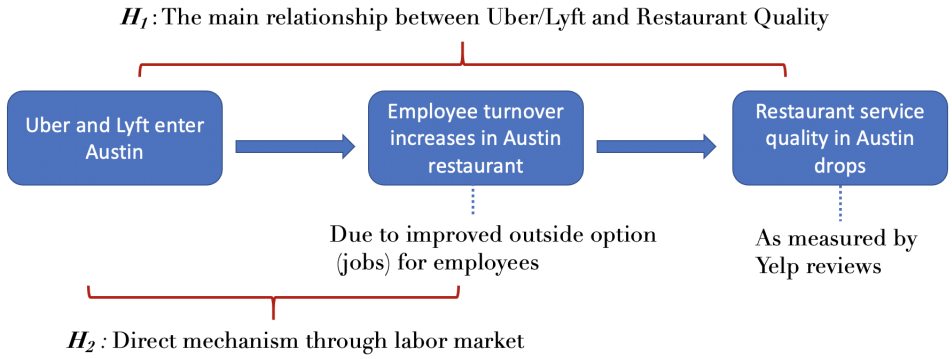


Figure 2: Two main hypotheses to test. H_1: Uber and Lyft's return to Austin led to a drop in the service quality as measured by Yelp reviews. H_2: Uber and Lyft's return to Austin increased employee turnover at restaurants.

Figure 2 schematically illustrates the relationship between H_1 and H_2. After empirically establishing the relationship between Uber and Lyft's presence and the restaurant's service quality utilizing the natural experiments in Austin areas (H_1), we further explore the mechanism underlying this relationship through formally investigating H_2. Our mechanism is based on employee turnover. If H_2 is correct, one would expect that an increase in the employee turnover for the Austin's restaurants must have led to a decrease in the service quality provided by those restaurants (Hurley and Estelami 2007; Hancock et al. 2013; Call et al. 2015).

The combination of H_1 and H_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, lead 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, both when describing our data and when conducting the empirical analysis, we start examining by H_1 which pertains to the *overall impact* of rideshare on service quality. We then turn to H_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 Datasets: Yelp Reviews and Employee Turnover

In order to test H_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 will describe later, we also use similar methods to obtain quality measures for attributes other than service (e.g., food). In order to study H_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 6.2, 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. Below, we describe these two data sets in further detail.

Yelp Review Data

Overview. The unit of observation in our Yelp reviews 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 a single dollar sign $ for cheap restaurants, two dollar signs $$ for mid-tier ones, and three dollar signs $$$ 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 dataset. 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]

[12] Review texts are the best available source for eliciting attribute level performance proxies for restaurants and attribute-level sentiments in reviews have 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).

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 attributes 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 pre-defined "dictionary" of words that have to do with service or food (Taddy 2013).

The second step takes each sentence and then 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 pre-defined dictionary and (ii) applying multipliers in order to correct for "valence shifters" such as negations, intensifications, and downtonwers. Ultimately, a sentiment score is assigned to each sentence.

Finally, equipped with a method to score sentiments of individual sentences, we arrive at an overall sentiment score for the entire review. Similar to the literature (e.g., Berger et al. 2010), we decide it using a majority vote rule where the overall sentiment will be the same as the score with more occurrences. The overall score 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 positive regarding food but negative regarding service.

Summary Statistics. Table 1 shows some descriptive statistics for Yelp reviews data. It provides summaries at the review level and the restaurant level for cities of Austin and Dallas, and for three periods: before Uber and Lyft Left the city (i.e., May 2014 - May 2016), during the time that Uber and Lyft were gone (i.e., May 2016 - May 2017), and after the two rideshare platforms returned to

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

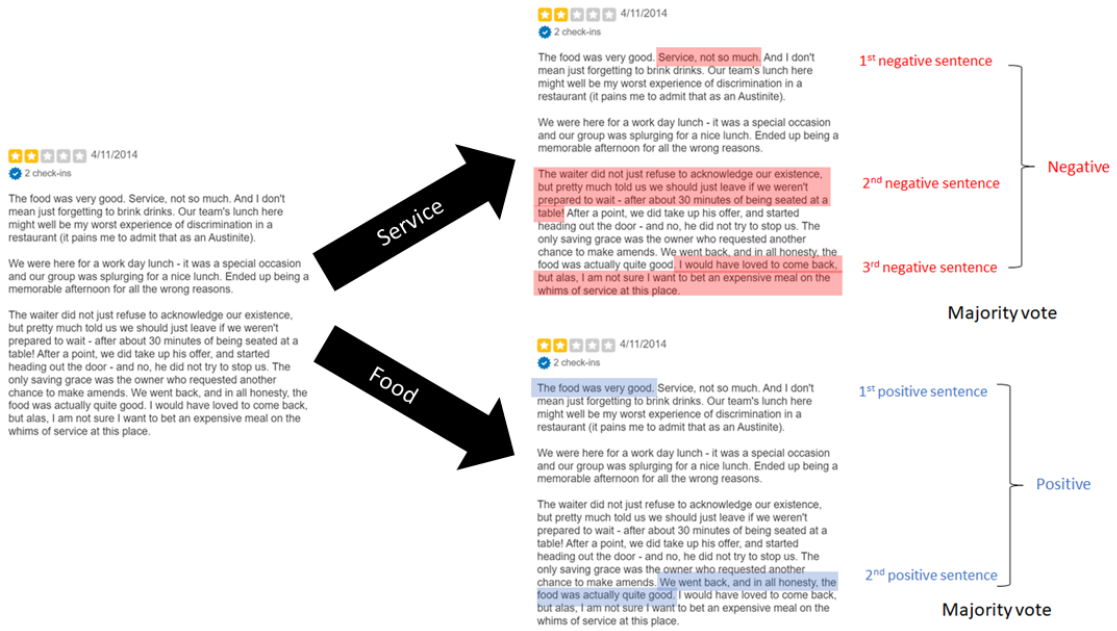


Figure 3: Illustration of Review-level Classification by Attribute

the city (i.e., May 2017 - May 2019).

Employee Turnover Data

Overview. Our second dataset contains detailed information on employees of different restaurants in Austin and Dallas. The unit of observation is employee-month. For each employee i 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 dataset, which prevents us from being able to merge this dataset with our Yelp Reviews dataset. 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 will allow 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.

[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 shift. The wage is coded as average hourly wage in their work shift.

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

Table 1: Summary statistics in Yelp data

Restaurant-level

	Total	Before (2014/May-2016/Apr)	Event (2016/May-2017/May)	After (2017/Jun-2019/May)
Austin, TX				
# of restaurants	632	632	632	632
One-Dollar restaurants	328	328	328	328
Two-Dollar restaurants	278	278	278	278
Three-Dollar restaurants	26	26	26	26
Monthly # 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, TX				
# of restaurants	501	501	501	501
One-Dollar restaurants	81	81	81	81
Two-Dollar restaurants	382	382	382	382
Three-Dollar restaurants	41	41	41	41
Monthly # 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/Jun-2019/May)
Austin, TX				
# of reviewers	72,331	30,828	19,746	36,372
# of reviews	168,086	68,484	34,544	65,058
% reviews related service	0.560	0.561	0.559	0.561
% reviews related 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, TX				
# of reviewers	87,576	37,737	22,736	44,357
# of reviews	201,910	84,582	38,930	78,398
% reviews related service	0.572	0.569	0.572	0.574
% reviews related 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)

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.

Table 2: Summary statistics in Turnover data

Restaurant-level

	Total	Before (2014/May-2016/Apr)	Event (2016/May-2017/May)	After (2017/Jun-2019/May)
Austin, TX				
# of restaurants	349	349	349	349
Size of workforce				
Average (*SD*)	16.23 (17.36)	12.01 (14.51)	18.58 (19.57)	18.12 (17.68)
Minimum	1	1	1	1
Maximum	199	182	199	124
Dallas, TX				
# of restaurants	296	296	296	296
Size of workforce				
Average (*SD*)	22.06 (16.73)	17.62 (13.90)	24.35 (16.73)	24.64 (18.04)
Minimum	1	1	1	1
Maximum	180	180	146	169

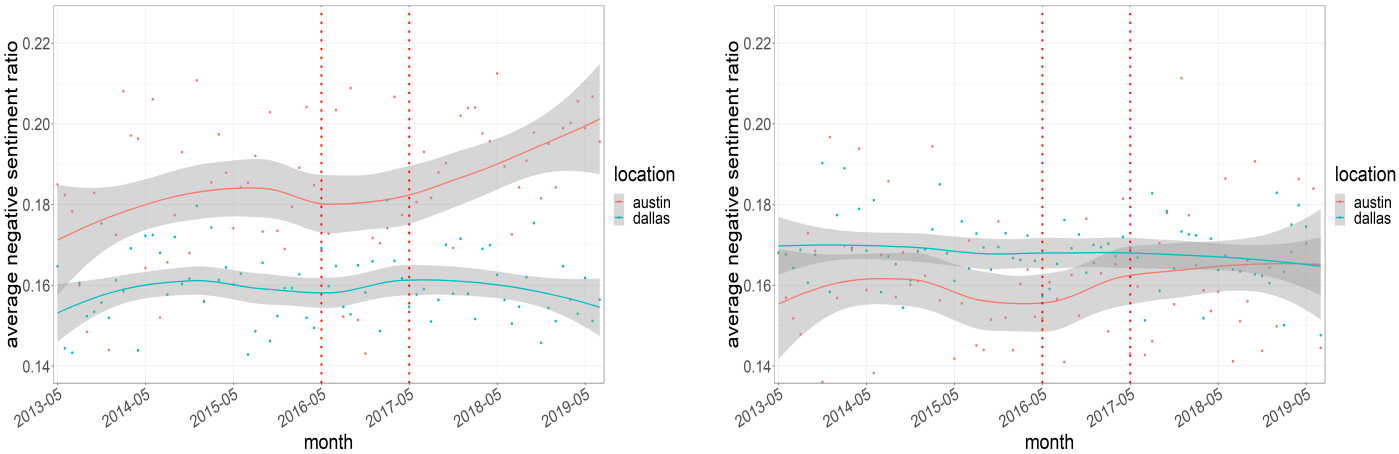
Worker-level

	Total	Before (2014/May-2016/Apr)	Event (2016/May-2017/May)	After (2017/Jun-2019/May)
Austin, TX				
Hourly wage ($)				
Average (*SD*)	11.8 (3.2)	10.8 (3.2)	11.7 (3.4)	12.2 (2.9)
Minimum	7.0	7.0	7.0	7.0
Maximum	28.8	28.4	28.8	28.2
Tenure (month)				
Average (*SD*)	5.1 (5.6)	4.8 (5.7)	5.3 (5.8)	5.1 (5.8)
Minimum	1	1	1	1
Maximum	60	60	36	24
Dallas, TX				
Hourly wage ($)				
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

*Note: Sample consists of worker/restaurant/month observations of 382,364 and the number of workers who work at least one month is 57,986. Size of workforce refers to the number of workers in each restaurants at each month. The change in the size of workforce can result from either more employment or higher turnover. Many workers are coded as being paid less than the minimum wage in Texas because they are tipped employees. Tenure is calculated based on the start time of employment and the maximum value of tenure is right-censored. In addition, to make the average and standard deviation of tenure more meaningful, those are calculated based on workers who quit within 2 years since the start time of employment.

3.4 Descriptive Data Patterns

Before turning to the empirical analysis, we show some informative data patterns motivating our study. The left panel of figure 4 shows the percentage of reviews that are negative toward service for Austin and Dallas over time. Each dot represents a monthly average for all the restaurants in each city. As the figure suggests, average sentiments in the two cities move roughly in parallel to each other until Uber and Lyft return to the city of Austin. After that point, the average sentiments begin to diverge. This is suggestive that Uber and Lyft's return to Austin negatively impacts the quality of service in the city's restaurants.



Topic: Service

Topic: Food

Figure 4: Time Trend of Negative Sentiment for each topic

The divergent patterns observed for service quality are not observed for food quality. As the right panel of figure 4 shows, the average sentiments towards food quality move in parallel to each other for the duration of our analysis. This suggests that the impact of Uber and Lyft on product quality must have happened through a channel that has to do more with service than with food.

In our analysis in subsequent sections, we will argue that this channel is employee turnover, and that the turnover of waitstaff is more likely to be influenced by gig work opportunities compared to turnover of chefs. We formalize the informal arguments Figure 4 helps put forth by first studying our hypothesis H_1 using Yelp reviews data. We then move to examining H_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 (H_1), taking advantage of the exogenous exit and re-entry 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.

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

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. Indicator $I(t \in \text{Before})$ is a binary variable which assumes the value of 1 only if t happens before May 2016 which was when Uber and Lyft left the city of Austin. Similarly, indicator $I(t \in \text{After})$ is a binary variable which assumes the value of 1 only if t happens after May 2017 which was when Uber and Lyft re-entered 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,

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

As we discussed 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 and Lyft's presence in Austin affects the quality of

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	0.006
	(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. $^{**}p<0.05$; $^{***}p<0.01$

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 from (1) to (4) 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 Austin Dummy. Given that the data are in panel form, we allow for fixed effect for time (2), for restaurant (3), and for both (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 in the paper (both for 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 and Lyft's exiting the city. In contrast, we found 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 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 percent, 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 re-entry 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 will focus on the regression with both fixed effects specification (in the last 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 would 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 to have more promising careers in the restaurant industry, relative to the wait-staff who are mostly in charge of service.[18] Consequently, we expect those workers to be less affected by the opportunity to drive for Uber and Lyft, relative to workers such as wait-staff.

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 below. It shows that β_2 (which captures the effect of Uber and Lyft's return to the city on the food quality) become non-significant 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 Uber 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 hypothesized that the food quality would be less influenced by the presence of Uber and Lyft than the service quality because of the different natures

[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 chef belong 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 chef in the future.

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			

of two labor forces for the front of the house labor 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 wait-staffs. 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 examine 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 would expect the impact of Uber and Lyft's presence on service quality to be more pronounced for restaurants whose service workers are less paid. 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: 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. $^{**}p<0.05$; $^{***}p<0.01$

Table 5 shows the result for low-tier (cheaper) one dollar restaurants.

Similar to the previous study, for low-tier (cheaper) one-dollar restaurants, β_1 is non-significant 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 points increase in the difference between the likelihood that review written for a one-$ restaurant in Austin contains a complaint about service and the likelihood that the same happens with a one-$ restaurant in Dallas (in column (4) with both fixed effects). In contrast, when we run the same regression for two to three-dollar 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 qualities of services 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 was that service quality drops because retaining service employees would be harder for low-tier restaurants when employees have gig-work opportunities as attractive outside options. As such, it would be reasonable to expect the effect to be stronger for one-$ restaurants whose

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 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, 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 and Lyft's return to the city and the restaurant's service quality. Also, Uber and Lyft's impact was more pronounced for cheaper restaurants whose service workers are more likely to be lured by gig-work opportunities. In particular, our finding that Uber and Lyft's return to the city affects the 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

[19]There can be a concern about the price compound. 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 dataset. We checked the stability of the restaurant dollar sign in Yelp by studying the historical snapshot of Yelp datasets. We indeed found 99.96% of dollar signs remain constant between Nov.2018 and Jan.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 footnote 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

our second hypothesis (H_2) more formally – whether employee turnover in the restaurant industry has been affected in Austin by the presence of rideshare companies to provide such direct evidence using a different dataset.

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 staff turnover in local restaurants due to the return of rideshare companies. We build parallels to those conducted using Yelp reviews 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 which depends only on τ_{itn}, how long employee n has been working at restaurant i when s/he is observed in period t. The second term, $e^{X_{itn}\beta}$, is parameterically 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:

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

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

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.

Table 7: Turnover Rate Analysis

	Dependent variable:
	Turnover hazard probability
AvgHourlyWage	-0.049^{***}
	(0.003)
Austin Dummy × Before Uber/Lyft exit	0.069
	(0.059)
Austin Dummy × After Uber/Lyft return	0.112^{**}
	(0.052)
Restaurant Fixed Effect	Y
Monthly Fixed Effect	Y
Observations	551,874
(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 non-significant in all of the estimated models. More interestingly, in line with our hypothesis (H_2), β_2 is positive and significant. This roughly means that the presence of Uber and Lyft in Austin increases the probability that a given restaurant worker quits in a given month by about 11.2% (note that this is percent, and not percentage point).

To get a sense of the magnitude of this effect in dollar terms, one can compare the estimated $\beta_2 = 0.112$ to the estimated effect of hourly wage on hazard rate ($\beta_0^{wage} = -0.049$). From table 7, one can calculate that the effect of Uber and Lyft's return to Austin was equivalent to that of a uniform \$2.29 decrease in hourly wages (i.e., $\beta_2/\beta_0^{wage} = -2.29$). This amounts to about 19% 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 would increase on average 19% 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, due likely to the fact that service workers are paid lower wages

Table 8: Turnover Rate by Worker Job Position

	Dependent variable: Turnover hazard probability	
	Front-of-House workers	Back-of-House workers
AvgHourlyWage	-0.076^{***}	-0.109^{***}
	(0.010)	(0.005)
Austin Dummy × Before Uber/Lyft exit	0.026	0.108
	(0.070)	(0.067)
Austin Dummy × After Uber/Lyft return	0.159^{**}	0.079
	(0.073)	(0.050)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	272,650	279,224
(Pseudo) R^2	0.047	0.064

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

than chefs and are, hence, more likely to switch to gig work. Here, we conduct two corresponding analyses.

First, we formally compare the pattern of turnover between two different positions in restaurants. We would expect the effect of Uber 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 to 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 ($\beta_2 = 0.159$) but non-significant for back of house workers. This is similar to the results from Yelp data showing that the effect of Uber and Lyft's presence is significant on service quality only, not food quality.

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 which of the following categories each restaurant belongs to – "Quick Service," "Fast Casual," "Casual Dining," "Upscale Casual," and "Fine Dining." This categorization of the restaurants approximately resembles the price-tier of the restaurants. Similar

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

Table 9: Turnover Rate by Restaurant Tier

	Dependent variable: Turnover hazard probability	
	Low-tier (Quick service, Fast casual)	High-tier (Casual dining, Upscale casual, Fine dining)
AvgHourlyWage	-0.076^{***}	-0.048^{***}
	(0.010)	(0.003)
AustinDummy × Before Uber/Lyft exit	0.171^{**}	0.030
	(0.080)	(0.069)
AustinDummy × After Uber/Lyft return	0.299^{***}	0.052
	(0.107)	(0.055)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	127,146	424,728
(Pseudo) R^2	0.065	0.050

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

to the analysis using a dollar sign in Yelp, we split the sample by the restaurant category into two broad groups: A low-tier restaurant group for Quick Service and Fast Casual, 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 interpreted the results from a tier-based analysis of reviews demonstrated in Table 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 and Lyft's presence on service quality to be more pronounced for restaurants whose service workers are less paid.[21]

[21] 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 will 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 dataset. In our dataset, we have a total of 150,000 workers. We observed about 9% of workers (i.e., 14,000 workers) changed their jobs (restaurants) at least once (i.e., workers quitted at one restaurant and later worked for another restaurant in our dataset). We calculate the conditional probability of job-switching between different restaurant tiers in our dataset. Most workers who had changed their jobs switched restaurants only in 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.

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 data and employee turnover data. In this section, we overview a series of those robustness checks, the details of which are relegated to Appendix A. 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 effecct of this "placebo" treatment to be statisticcally non-significant. The regression results (presented in detail in the appendix) confirm this expectation for both the reviews data and the 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 the sentiments of reviews on 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 and Lyft's presence on the 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 dis-aggregate 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 non-significant. We do this both for the reviews data and for 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 level and confirm that indeed prior to the return of Uber and Lyft to Austin, the trends of review sentiments about service are parallel between Austin (treatment city) and Dallas (control city).

7. **Quality vs. 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 employees data. In particular, we use the number of workers at each restaurant in each month as a dependent variable. DiD analysis shows that Uber and Lyft's presence in the city of Austin has a negative impact on this variable as well. As for "worker quality", we studied the change in a worker hazard rate to examine the impact of ride-sharing 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 vs. 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-run or long-run effect. We examines

the effect on employee tunrover, worker size, and average hourly wage. We first find that effect on the turnover is reasonably long-run but is attenuated over time. The result further reveals that the worker-quantity impact of Uber and Lyft's presence in the market is weaker in the second year after their return compared to 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. Though this may have been a response to the effect of Uber and Lyft, we argue that one should use caution in interpreting this result causally. This is due in part to the fact that 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 and Lyft's presence makes restaurant jobs less desirable. Given that we have only two years of data, it is difficult to conclude whether the effect is more like a short term or a long term one. But one consistent interpretation is that when the employee turnover is high, not only does the quantity of 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 seems insufficient. The effects of Uber and Lyft would persist and would not be driven away by the wage correction, although it may alleviate over time.

9. **Direct relationship between turnover and Yelp reviews:** The mechanism we propose for the impact of Uber and Lyft on service quality 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 co-move. 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 would be 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. Potential impact of the gig economy on other parts of the economy through demand-side channels has been documented before (e.g Burgdorf et al. 2019, Zhang et al. 2018, Hampshire et al. 2018). As such, in this section, we perform some analyses to study whether Uber and Lyft's return to Austin may have impacted 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 above hypothesis does not explain some of the evidence we have already presented in the paper. First, tables 5 and 6 show that the impact of Uber and Lyft's presence on perceived service qualities of restaurants is significant only for one-dollar-sign restaurants but 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, non-significant. As we discussed 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 would have 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 the above hypothesis. The first type is similar to what we mentioned above: 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 ridesharing platforms on the reach of travel has been 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 Jan/2017. We have observations in only two cities, Austin and San Antonio in this data, so we compare two cities in this analysis[22].

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.[23] As table 10 below shows, the effect is small in magnitude and statistically non-significant. 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 and Lyft's presence on the service quality of some restaurant types arises mainly from supply-side forces rather than demand-side ones.

[22]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 restaurants data to directly conduct a similar DiD we did in our main analysis. Instead, we use San Antonio as an alternative control city here. As the robustness check shows in Appendix A-5, our results are still significant when we change the control city from Dallas to San Antonio.

[23]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 and Lyft's exit in 2016.

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:	**p<0.05; ***p<0.01

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 while 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 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. We exploit a natural experiment in which, due to regulatory changes, Uber and Lyft exited the market in Austin, TX, 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 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 to 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 dataset of restaurants in Austin and Dallas from 2014-2019. Turnover rates increase in Austin relative to Dallas once Uber and Lyft return. The magnitude of this effect is estimated about 19% 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-end or high-end restaurants; likewise, it is observed only for front-of-house workers, while 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 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 the gig work may shape the future economy.

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Appendix

A Robustness Checks

In this section, we provide details for the robustness checks outlined in Section 6 of the main text.

A.1 "Placebo" treatment timing

Robustness check for analysis of Yelp reviews. We run a DiD regression of our measure of service quality Y_{it} between Austin and Dallas before and after a "placebo" shock with an ad-hoc time. We choose May 2018. The following regression captures the analysis:

$$Y_{it} = \alpha_i + \tau_t + \beta_1 \cdot I(t \in \text{After Ad-hoc Time}) \cdot I(i \in \text{Austin}) + \epsilon_{it} \tag{5}$$

The coefficient of interest here is β_1. Table 11 shows the results. As can be seen from the table, β_1 is estimated to be less than 1% both for service and for rood; and both estimates are statistically non-significant.

Table 11: Ad-hoc timing Regression of Yelp data

	Dependent variable:	
	Ratio of Complaints on Service	Ratio of Complaints on Food
Austin Dummy × Ad-hoc Timing Dummy	0.002	−0.0003
	(0.007)	(0.007)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	23,722	23,722
R^2	0.168	0.090
Adjusted R^2	0.127	0.045

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

Robustness check for the employee turnover analysis. Similarly, we repeat the analysis of employee turnover with a placebo shock time. Table 12 shows the results. Again, as expected, the coefficient on "Austin Dummy × May/2018-May/2019" is small and statistically non-significant.

A.2 Changing the control topic

In one of our analyses of Yelp reviews, we used food as the "control topic." That is, we ran a DiD analysis of the city of Austin and showed that Uber and Lyft's presence in the city leads to more negative reviews on service quality compared to food quality. In this robustness check, we study

Table 12: Ad-hoc timing Regression of Turnover data

	Dependent variable:
	Turnover hazard probability
AvgHourlyWage	-0.046^{***}
	(0.003)
Austin Dummy × May/2018-May/2019	−0.040
	(0.057)
Restaurant Fixed Effect	Y
Monthly Fixed Effect	Y
Observations	197,100
(Pseudo) R^2	0.113

**p<0.05; ***p<0.01

a different control topic: ambience. Table (13) shows the results. As can be seen there, our DiD coefficient is still statistically significant and has the same size and rough magnitude.

Table 13: Difference-in-Difference in *Ambiance*

	Dependent variable:
	Ratio of Complaints on Ambiance
Austin Dummy × Before Uber/Lyft exit	0.0002
	(0.001)
Austin Dummy × After Uber/Lyft return	0.002
	(0.001)
Restaurant Fixed Effect	Y
Monthly Fixed Effect	Y
Observations	58,227
R^2	0.030
Adjusted R^2	0.010

**p<0.05; ***p<0.01

A.3 Keyword selection for each Topic

In this robustness analysis, we change the dictionaries that we used to identify whether a sentence in a review is related to service or food. The dictionaries that we used for our analysis in the main text were as follows. (1) Service: staff, waiter, waitress, service, waiting, server, worker, stood, dirty, wait, counter, ignore, and (2) Food: food, mouth, melt, delicious, unpalatable, appeti, cooked, edible, taste, tasty, bread, meat, steak, dessert, vege, flour, corn, pizza, mexican, egg, sushi.

In this robustness check, we use a broader dictionary instead. The new dictionaries are as follows. (1) Service: staff, waiter, waitress, service, waiting, server, worker, stood, dirty, wait, counter, ignore, minute, line, clean, and (2) Food: food, mouth, melt, delicious, unpalatable, appeti,

cooked, edible, taste, tasty, tast, bread, meat, steak, dessert, vege, flour, corn, pizza, mexican, egg, sushi, flavor, sweet, yum, juicy, spicy, bland.

Table 14 shows the result from our main DiD analysis with the new dictionaries. As can be seen from this table, the DiD coefficient for service is statistically significant with a similar magnitude to what we obtained in our main analysis. Also, the DiD coefficient for food is non-significant, similar to the result we had in the main text of the paper.

Table 14: Robustness check for keyword selection

	Dependent variable:	
	Ratio of Complaints on Service	Ratio of Complaints on Food
Austin Dummy × Before Uber/Lyft exit	−0.005	−0.001
	(0.006)	(0.006)
Austin Dummy × After Uber/Lyft return	0.012**	0.005
	(0.006)	(0.006)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	58,227	58,227
R^2	0.254	0.110
Adjusted R^2	0.239	0.091

**p<0.05; ***p<0.01

A.4 Alternative Measurements of Service/Food Quality from Reviews

In our main analysis of Yelp reviews, we took one specific approach to measuring food or service quality based on reviews. In this section of the appendix, we explore some alternatives.

Alternative Aggregation Levels. In the main analysis, we aggregated the reviews up to the restaurant-month level. In this robustness check, we aggregate reviews up to the restaurant-year level instead, and we run similar DiD regressions for service and food quality. Table 15 presents the results and shows that they are robust to this change in the aggregation level. Overall, we see similar results to before albeit with less statistical significance, which should not be surprising as the number of observations has decreased by an order of magnitude.

Table 15: Robustness check for the yearly level aggregation

	Dependent variable:	
	Ratio of Complaints on Service	Ratio of Complaints on Food
Austin Dummy × Before Uber/Lyft exit	−0.001	−0.005
	(0.008)	(0.008)
Austin Dummy × After Uber/Lyft return	0.015**	0.007
	(0.007)	(0.007)
Restaurant fixed effect	Y	Y
Yearly Fixed effect	Y	Y
Observations	5,393	5,393
R^2	0.599	0.414
Adjusted R^2	0.495	0.262

**p<0.05; ***p<0.01

The above approach presents results from further aggregation of reviews relative to what we worked with in the main text of the paper. We next turn to the flip side of this; we do not aggregate the reviews. Thus, instead of the restaurant-month level, this new analysis will be implemented at the restaurant-review level. The results are presented in table 16. As this table suggests, our results are robust.

Table 16: DiD at the review level

	Dependent variable:	
	Binary Index of Each Review	
	(Neg) Service	(Neg) Food
Austin Dummy × Before Uber exit	0.077**	0.030
	(0.032)	(0.033)
Austin Dummy × After Uber return	0.076**	0.042
	(0.032)	(0.033)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	281,136	281,136
Note:		**p<0.05; ***p<0.01

Absolute vs. Relative Number of Negative Reviews. Our main analysis measures how negative the sentiment is for service by examining what percentage of reviews that mentioned service were negative (same applies to food). Another possible approach would be to use absolute numbers of negative reviews instead of relative ones. Table 17 shows our results are by and large robust to this, both when we control for the total number of reviews and when we do not.

Table 17: Using absolute rather than relative number of negative reviews to measure sentiment toward service or food

	Dependent variable:	
	# of negative reviews	
	(*Service*)	(*Food*)
# of reviews	0.166***	0.154***
	(0.006)	(0.004)
Austin Dummy × Before Uber exit	0.047*	0.016
	(0.025)	(0.023)
Austin Dummy × After Uber return	0.053**	0.034
	(0.024)	(0.022)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	58,227	58,227
R^2	0.422	0.380
Adjusted R^2	0.410	0.368
Note:	**p<0.05; ***p<0.01	

Accounting for Review Sizes and Details. One potential concern with our construction of the dependent variable Y_{it} in the DiD analysis is that it gives the same weight to all reviews irrespective of how long they are. In reality, however, it may be that long reviews with multiple complaints about the service indicate a more negative attitude relative to a short review with one complain only. Thus, one question is whether taking this matter into account impacts our results.

To investigate this, we formulate an alternative measure for Y_{it}. Here, we keep the analysis at the restaurant-month level, but calculate Y_{it} differently. In this new approach, we pool together all of the reviews written for restaurant i during month t, and we treat them as a single corpus. We then determine whether or not this single text is negative toward service (or food) in the same way as we did for each single review in the main analysis.[24] With this method, long and detailed negative or positive reviews contribute more to the final classification of the corpus as negative or positive, relative to shorter reviews. The results are provided in table 18 which, again, suggests our main insights are robust to this change in the measurement approach.

A.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.

Yelp reviews. Our DiD analysis of Yelp reviews was performed using Austin as the treatment

[24]The result is that each Y_{it} is now either 0 or 1.

Table 18: Alternative method to defining the review sentiment in order to take into account different review lengths

	Dependent variable:	
	(Service) New measure	(Food) New measure
Austin Dummy × Before Uber exit	0.010	0.001
	(0.009)	(0.008)
Austin Dummy × After Uber exit	0.019**	0.005
	(0.009)	(0.007)
Restaurant Fixed Effect	Y	Y
Monthly Fixed Effect	Y	Y
Observations	58,227	58,227
R^2	0.085	0.059
Adjusted R^2	0.066	0.040
Note:		**p<0.05; ***p<0.01

city and San Antonio as the control city. Here, we perform two further analyses. First, we change the control city from Dallas to San Antonio. We expect the DiD results to be still significant. Second, we change the treatment city from Austin to Dallas. We expect the DiD coefficient to be non-significant. Table 19 reports the results and confirms both of our expectations.

Table 19: Robustness check for Regional DiD (Other City)

	Dependent variable:	
	Ratio of Complaints on Service	
Austin Dummy × Before Uber/Lyft exit	0.010	
	(0.007)	
Austin Dummy × After Uber/Lyft return	0.022***	
	(0.007)	
San Antonio Dummy × Before Uber/Lyft exit		−0.001
		(0.006)
San Antonio Dummy × After Uber/Lyft return		−0.006
		(0.006)
Sample Region	Austin & San Antonio	Dallas & San Antonio
Monthly fixed effect	Y	Y
Restaurant fixed effect	Y	Y
Observations	33,041	55,190
R^2	0.133	0.116
Adjusted R^2	0.113	0.099
		**p<0.05; ***p<0.01

Employee Turnover. We conduct similar robustness tests with the employee turnover data. Again, as table 20 shows, the DiD coefficient when Austin and San Antonio are compared is significant, while the same coefficient when Dallas and San Antonio are compared is non-significant, which we expect.

Table 20: Robustness check for Turnover DiD:

Left column uses Austin as the treatment group and San Antonio as the control group. Right column uses San Antonio as the treatment group and Dallas as the control group.

	Dependent variable:	
	Turnover hazard probability	
AvgHourlyWage	-0.079^{***}	-0.046^{***}
	(0.004)	(0.002)
Austin Dummy × Before Uber/Lyft exit	0.046	
	(0.060)	
Austin Dummy × After Uber/Lyft return	0.106^{**}	
	(0.052)	
San Antonio Dummy × Before Uber/Lyft exit		−0.006
		(0.059)
San Antonio Dummy × After Uber/Lyft return		0.036
		(0.055)
Sample Region	Austin & San Antonio	Dallas & San Antonio
Monthly Fixed Effect	Y	Y
Restaurant Fixed Effect	Y	Y
Observations	386,241	560,100

**p<0.05; ***p<0.01

A.6 Parallel Trends Analysis

Figure 7 plots the DiD coefficient in our analysis of service quality (comparing Austin and Dallas) at a yearly level. As can be seen from this figure, the coefficient is non-significant in each year prior to re-entry of Uber and Lyft to Austin, as well as in each year after their return.

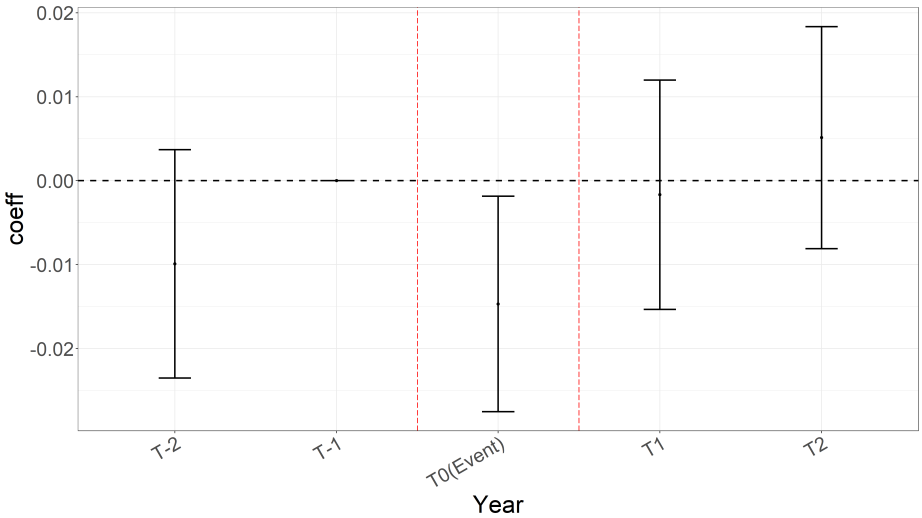

Figure 7: Testing Parallel Trend

Notes: The figure plots the estimated β_k from $Y_{it} = \alpha_i + \tau_t + \sum_{k=-2}^{2} \beta_k I(i \in \text{Austin}) \times \text{Year}_k + \epsilon_{it}$. Standard errors are clustered by restaurant-level and 95% confidence intervals are presented.

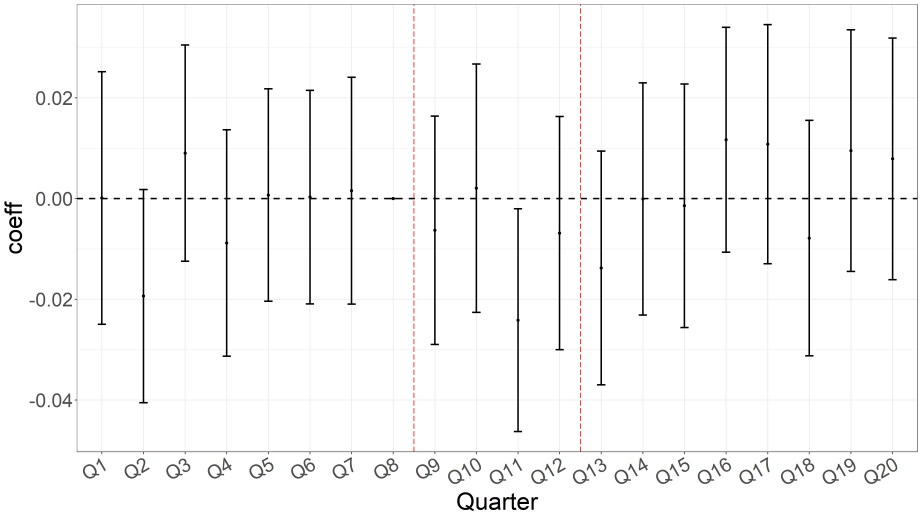

Figure 8: Quarter-Level Parallel Trend Test

A noteworthy feature of this parallel-trends analysis is that it has been conducted at the annual level. This is at odds with our main analysis in the paper which was conducted at the monthly level. Ideally, we would have preferred to carry out the parallel-trends analysis also at the monthly level. Nevertheless, data limitations prevents us from doing so. The number of observations is simply not enough to support a parallel trends analysis at such a granular level which leads to more than 60 coefficients of interest. For the sake of completeness, however, we do carry out this analysis at a finer level as shown in figure 8. This figure presents a quarterly level parallel trends analysis. Although suggestive of parallel trends, the results seem too noisy to deliver a reliable interpretation. We finish this section by noting that this paper is not the first to carry out its parallel-trends analysis at a coarser level than its main DiD analysis. For instances, Foltz and Opoku-Agyemang (2015) and Gorback (2020) conduct their main analyses at a more granular monthly-level, but did the parallel trend analysis at the yearly level.

A.7 Quality vs. Quantity of Workers and the Interpretation of the Underlying Mechanism

In the main text, we argue that higher employee-turnover rates for restaurants leads to lower service quality as measured by negative Yelp reviews. It is worth delving into the mechanism further.

In principle, 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," because workers leave the restaurant with shorter tenures and, hence, before they accrue enough

Table 21: DiD analysis with worker size as dependent variable

	Dependent variable:
	Worker size
Austin Dummy × Before Uber exit	-0.913^{***}
	(0.307)
Austin Dummy × After Uber return	-0.645^{**}
	(0.287)
Restaurant Fixed Effect	Y
Monthly Fixed Effect	Y
Observations	24,251
R^2	0.801
Adjusted R^2	0.796
Note:	**p<0.05; ***p<0.01

experience for delivering high-quality service. This latter issue (i.e., high employee turnover being linked to service quality through human capital) has been heavily studied in the literature (e.g., Hinkin and Tracey (2000)). As we will discuss in the next appendix section, the first effect may be relatively more short-run.

To examine the worker-size channel more closely, we repeat our main turnover DiD analysis but this time, we replace the dependent variable with the number of employees at each restaurant in a given month. The DiD results are given in table 21. As can be seen from these results, Uber and Lyft's presence does seem to have a negative impact on the size of restaurant workers. It is suggestive evidence that worker shortage might happen due to Uber and Lyft's presence. One caveat of this study is that we do not observe hours of work of restaurant workers. Restaurants facing worker shortage may ask existing workers to fill the empty shifts. This is beyond the scope of our data.

As for "worker quality", we studied the change in a worker hazard rate to examine the impact of ride-sharing companies on worker experience. Consistently, we here provide a different DiD analysis using a tenure period of each worker as a dependent variable.[25] The DiD results are given in table 22. It shows that restaurant workers starting their job in Austin after Uber and Lyft returned have a shorter tenure than those in Dallas at the time. This indicates that worker tenure gets shorter so that workers have less chance to accrue experience related to restaurant quality.

[25]The main DiD based on the turnover decision of workers can incorporate any monthly change with regard to Uber and Lyft. Here, when studying the tenure of each worker, we reshape our data based on the starting period of each worker and calculate their tenure.

Table 22: DiD analysis with worker tenure as dependent variable

	Dependent variable:
	Worker Tenure
Austin Dummy × Before Uber exit	0.163
	(0.106)
Austin Dummy × After Uber return	-0.308^{***}
	(0.119)
Restaurant Fixed Effect	Y
Period Fixed Effect	Y
Observations	49,626
R^2	0.035
Adjusted R^2	0.026
Note:	**p<0.05; ***p<0.01

A.8 Short vs. Long Term Effects

One question that arises about our analysis is whether the impact of Uber and Lyft on the labor market is more a short-run or long-run effect. A limitation of our analysis is that the treatment (i.e., Uber and Lyft's exit from the city of Austin) lasted only about a year. This restricts our ability to conduct a more detailed analysis of short vs. long run effects of the treatment. An alternative, however, is available. We examine the effects of Uber and Lyft's return to Austin, for which we have two years of data.

We first examine the effects of Uber and Lyft's return on our main labor-market variable of interest: employee turnover. To this end, we limit the date to months during and after Uber and Lyft's exit, and do the same DiD analysis as before with some modifications: we conduct the analysis at the yearly level, we set the omitted group to be the year when Uber and Lyft were absent, and, most importantly, we use two "after×Austin" interaction coefficients one for each year, instead of using only one overall coefficient. The results are given in table 23, which are suggestive that the effect is reasonably long-run but is attenuated over time. Obviously, this claim does not extend beyond two years given our data limitations.

In addition, we repeat the same analysis but with different dependent variables. We examine patterns regarding average hourly wage and worker size. Results are presented in tables 24 and 25. As can be seen from these results, the worker-size effect of Uber and Lyft's return to Austin is statistically significant for the first year after return but not during the second year. The result for wages is the opposite: the first year interaction effect is not significant but the second year effect is.

Table 23: Short vs. Long term changes in Turnover

	Dependent variable:
	Turnover hazard probability
Event Period (Baseline)	
Austin Dummy × One-year after Uber return	0.060**
	(0.029)
Austin Dummy × Two-year after Uber return	0.048*
	(0.027)
Monthly Fixed Effect	Y
Restaurant Fixed Effect	Y
Observations	321,855
(Pseudo) R^2	0.067
Note:	; **p<0.05; ***p<0.01

Table 24: Short vs. Long term changes in Wage

	Dependent variable:
	Wage
Event Period (Baseline)	
Austin Dummy × One-year after Uber return	−0.058
	(0.069)
Austin Dummy × Two-year after Uber return	0.387***
	(0.107)
Monthly Fixed Effect	Y
Restaurant Fixed Effect	Y
Observations	14,252
R^2	0.862
Adjusted R^2	0.857
Note:	**p<0.05; ***p<0.01

Table 25: Short vs. Long term changes in Worker Size

	Dependent variable:
	Worker Size
Event Period (Baseline)	
Austin Dummy × One-year after Uber return	−0.887***
	(0.304)
Austin Dummy × Two-year after Uber return	−0.350
	(0.311)
Monthly Fixed Effect	Y
Restaurant Fixed Effect	Y
Observations	14,252
R^2	0.868
Adjusted R^2	0.863
Note:	**p<0.05; ***p<0.01

Given that we have only two years of data, it is difficult to conclude whether the effect is more like a short term or a long term one. But one consistent interpretation is that Uber and Lyft's return to the city of Austin leads to a shortage of restaurant workers in the short run which later dwindles due potentially to a market response through correcting restaurant wages. But, again, this interpretation involves a strong assumption that the wage response is large enough in magnitude. That said, a simple calculation strongly suggests that this wage response is too small in magnitude for its effects to be of importance in our analysis. The "Two-years after × Austin" coefficient in the wage DiD regression comes back at about 40 cents per hour. This is only about 17% of the amount (i.e., $2.29) by which Uber and Lyft's presence makes restaurant jobs less desirable for workers according to our estiamtes from table 7.

Therefore, when the employee turnover is high, not only does the quantity of 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 seems insufficient. The effects of Uber and Lyft would persist and would not be driven away by the wage correction, although it may alleviate over time.

A.9 Direct Relationship between Turnover and Yelp Reviews

The mechanism we propose for how Uber and Lyft impact restaurant service quality is one based upon a link between employee turnover and quality of service. This gives rise to the natural question that whether these two indeed correlate negatively with one another.

To investigate this question, we simply regress quality of service (and that of food as a control topic) on restaurant worker turnover rates. We do this for Back of House and Front of House workers separately. We expect the coefficient to be positive and significant for the FOH analysis on service but not for any of the other three resulting analyses. Tables 26 and 27 show that we indeed obtain the expected result.

Before closing this section, we need to emphasize that suggestive as they may be, these results cannot be interpreted causally. This is because there is no guarantee that the variation in turnover is exogenous. For instance, a management crisis in a restaurant can lead to both increased employee turnover and worsened service quality. Such endogenity concern is indeed the reason why we treat the analysis in this appendix section as a reassuring robustness check rather than a main analysis in the main text. In the main text of the paper, we rely on the exogenous variation provided by Uber and Lyft's entry and exit, which we consider crucial to our analysis.

Table 26: Testing for direct linkage between turnover and service (or food) quality: Back of House workers

	Dependent variable: (Back of House)	
	(Neg) Service	(Neg) Food
Constant	0.168^{***}	0.167^{***}
	(0.003)	(0.003)
Turnover monthly rate (BOH)	−0.001	−0.003
	(0.007)	(0.007)
Observations	58,227	58,227
R^2	0.00000	0.00000
Adjusted R^2	−0.00002	−0.00001
Note:		**p<0.05; ***p<0.01

Table 27: Testing for direct linkage between turnover and service (or food) quality: Front of House workers

	Dependent variable: (Front of House)	
	(Neg) Service	(Neg) Food
Constant	0.154^{***}	0.166^{***}
	(0.004)	(0.004)
Turnover monthly rate (FOH)	0.029^{***}	−0.001
	(0.008)	(0.008)
Observations	58,227	58,227
R^2	0.0002	0.00000
Adjusted R^2	0.0002	−0.00002
Note:		**p<0.05; ***p<0.01