COVID-19 and Digital Resilience: Evidence from Uber Eats[12]

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Abstract

We analyze how digital platforms can be a source of resilience for firms during a crisis by providing continuity in access to customers. Using novel order-level data from Uber Technologies, we study how the COVID-19 pandemic and the ensuing shutdown of businesses in the United States affected small business restaurant supply and demand on the Uber Eats platform. We find evidence that, despite widespread establishment closures and curtailment of supply hours, small restaurants experienced significant increases in total activity, orders fulfilled per day, and orders fulfilled per hour following the closure of the dine-in channel and we unpack the demand-side and supply-side shocks that contribute to these increases. Using a new robust measure of competition based on actual observed overlapping consumption across businesses, we further document an increase in the intensity of competitive effects following the shock, showing in the process that an increase in the number of providers on a platform can induce both market expansion and heightened inter-provider competition in a manner that may not align platform incentives with those of its complementors. Our findings underscore the critical role that digital technologies play in enabling business resilience in the economy and provide insight into how supply-side and demand-side factors shape business performance on a platform.

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[1] The authors are listed alphabetically by last name. This study was conducted as an independent research collaboration between the authors. Manav Raj and Arun Sundararajan are not and have not been affiliated with Uber Technologies, and Calum You is not and has not been affiliated with NYU. No consulting fees, research grants or other payments have been made by Uber Technologies to the NYU authors, or by NYU to the Uber Technologies author. We thank Arslan Aziz, Emilie Boman, Libby Mishkin, Sabrina Ross, Allison Wylie, participants at the 2020 Workshop on Information Systems and Economics and participants of the NYU Stern Future of Work seminar series for thoughtful feedback, and Uber Technologies for access to data. All errors are our own.

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1. INTRODUCTION

The COVID-19 pandemic acutely impacted the restaurant industry. As localities imposed shelter-in-place orders and consumers pulled back their presence in public spaces in the first half of 2020, restaurants that relied exclusively or primarily on dine-in were especially affected.[6] Numbers from the Advance Monthly Retail Trade Survey by the U.S. Census Bureau indicate a 48.7% year-over-year decline for food services and drinking places in April 2020, reflecting revenue losses of over $30 billion that month alone, and of over $50 billion in March and April 2020 (US Census Bureau Monthly & Annual Retail Trade, 2020). According to the National Restaurant Association, the average establishment saw a 78% decline in its revenues in the first 10 days of April 2020 compared to the same period in April 2019 (Grindy, 2020).

While larger restaurant chains had the resources to weather a prolonged economic downturn, independent establishments and mom-and-pop restaurants struggled to stay alive. Early estimates suggested that up to 75% of independent restaurants would not survive (Severson and Yaffe-Bellany, 2020), as the COVID-19 shock exacerbated the credit constraints (Evans and Jovanovic, 1989) that typically disadvantage small businesses which have limited access to alternative financing options during such crises (Dietrich, Schneider, and Stocks, 2020). Facing shutdown, restaurants were forced to utilize alternative channels to reach customers, maintain revenue, and survive. A bright spot for some restaurants was the growth in access to digital platforms like Seamless, DoorDash and Uber Eats in the years preceding COVID-19.

Our study takes a close look at the economic effects of access to these channels during the onset of the COVID-19 pandemic in March and April 2020, examining the stabilizing and sustaining effects of food delivery platforms in the weeks following the economic shutdown in the United States. We use order-level data from the Uber Eats food delivery platform for five major US cities (New York City, San Francisco, Atlanta, Miami, and Dallas) from February 1st through May 1st 2020 to examine changes in digital demand and performance following the shutdown. Across our five sample cities, we see that restaurants that remain open for delivery experienced significant and economically meaningful increases in the count of orders that they received. This increase in orders occurred despite many restaurants cutting the number of hours that they supply

[6] Appendix Figure A1 presents the year-over-year percent change in seated diners from mid-February to mid-April 2020.

on the platform, although perhaps aided by other restaurants shutting down their digital channel entirely. Probing deeper into the effects of the closure of a restaurant's competitors provides new evidence of potentially diverging incentives between a platform and its providers.

We contribute new findings to a growing literature that has explored the challenges and opportunities created by digital distribution channels for incumbent firms (e.g., Chen, Hu, and Smith, 2019a; Danaher *et al.*, 2010; Smith and Telang, 2009), and in particular, smaller businesses. For example, Airbnb is now a channel not just for sharing one's spare bedroom or apartment, but also for incumbent bed-and-breakfasts and full-time independent vacation rental properties (Guttentag, 2015). Similarly, e-commerce platforms such as eBay and Amazon.com have long been critical channels for small businesses and individual sellers (Bailey *et al.*, 2008). Our study underscores how COVID-19 has, correspondingly, now made food delivery platforms vital to small businesses in the restaurant sector.

Additionally, prior work has illustrated how the drivers of the net economic effects of a platform channel can be varied. On the supply side, digital distribution channels lower the costs of entry for small providers, enabling them to reach consumers more easily and providing them with flexibility (Chen *et al.*, 2019b; Einav, Farronato, and Levin, 2016). On the demand side, digital platforms greatly reduce the costs of consumer search and discovery using recommendation tools that leverage large data on consumer behavior with a wide inventory of products (Brynjolfsson, Hu, and Simester, 2011; Oestreicher-Singer and Sundararajan, 2012). The reduction in search costs and the ability to aggregate demand across a wider consumer base can be especially beneficial for "niche" offerings that may have previously been unknown or inaccessible to consumers (e.g., Brynjolfsson *et al.*, 2011; Dewan and Ramaprasad, 2012; Zhang, 2018).

Our analysis is the first to empirically resolve the net impact of potentially countervailing supply and demand aspects of the COVID-induced economic shock, which, a priori, appeared as if they might collectively either raise or lower online performance. The absence of dine-in options may shift demand towards the online channel; variability in the availability of groceries and fears of going to a grocery store may induce consumers to order in rather than cook themselves; an increase in the hours people have been spending at home coupled with health concerns associated with food prepared and delivered by people outside their homes could induce an increased propensity and ability to prepare one's own meals. We show that the net *demand-side* *shock* was consistently positive but varied substantially in magnitude across geographies, despite the likely negative demand spillovers from a *supply-side shock* induced by the shuttering of many restaurants and the cutting back of operating hours for those that remained open.

We then probe deeper into the competitive effects of this supply-side shock, adding to prior work that has examined how digital platforms alter the nature of competition (Animesh, Viswanathan, and Agarwal, 2010; Farronato and Fradkin, 2018; Filippas, Horton, and Zeckhauser, 2020a; Zervas, Proserpio, and Byers, 2017). We show that the intensity of inter-provider (restaurant) competition increased during the COVID-19 shock. We do so by constructing a new and more economically robust metric of competition based on actual overlapping consumption across businesses, and inferred from a bipartite graph (e.g., Bimpikis, Ehsani, and İlkılıç, 2019; Huang, Zeng, and Chen, 2007; Leiponen, 2008) of customers and restaurants. This new approach may independently contribute towards better measurement of platform-based inter-provider competition in future work. As one might expect, the performance of an individual restaurant on the Uber Eats platform is better when it faces less competition. However, overall demand on the platform is larger when more restaurants are open. These divergent effects of market expansion and inter-provider substitution provide new insight into the tension between what is optimal for a platform and what is optimal for its complementors.

Further, by illustrating how digital channels can stabilize firm performance when other distribution channels are limited, we add a new facet to a body of research on cannibalization and expansion due to digital distribution channels (Chen *et al.*, 2019a; Danaher *et al.*, 2010; Smith and Telang, 2009; Viswanathan, 2005; Yin *et al.*, 2009) and the interplay between platform-mediated and physical-world opportunities for small businesses (Han *et al.*, 2019; Kitchens, Kumar, and Pathak, 2018). Our investigation of the moderating effect of competition on performance on the digital platform adds to a body of literature that explores how digital technologies and distribution channels affect substitution and spillovers across competing firms (Haviv, Huang, and Li, 2020; Liang, Shi, and Raghu, 2019; Raj, 2021; Reshef, 2019; Tambe and Hitt, 2014). In addition, our analysis of the dual effects of market expansion and business stealing contributes to literature that discusses the tension between strategies that are optimal for the platform and strategies that are optimal for platform participants, complementors, and co-creators (e.g., Castillo, 2020; Ceccagnoli *et al.*, 2012; Filippas, Jagabathula, and Sundararajan, 2021b; Rietveld, Ploog, and Nieborg, 2020). Our work further adds to a new line of literature that seeks to understand how the COVID-19 pandemic affected small businesses (de Vaan *et al.*, 2020) and online channels (Han *et al.*, 2020) and presents practical implications for small businesses by highlighting how digital distribution channels can serve as a differentiating source of resilience during crisis.

The rest of this paper is organized as follows. Section 2 describes our empirical setting and data and presents model-free evidence. Section 3 outlines our models, results, and discusses their implications. Section 4 concludes and outlines directions for additional inquiry.

2. EMPIRICAL SETTING AND DATA

We study how digital channels can substitute for brick-and-mortar sales when traditional channels are disrupted using the economic lockdowns associated with the COVID-19 pandemic as an exogenous shock. As the COVID-19 virus began to spread across the United States in March 2020, states and cities requested or required that residents avoid any non-essential travel or activity (Mervosh, Lu, and Swales, 2020). Such “stay-at-home” or “shelter-in-place” orders, in conjunction with consumer anxiety and fear regarding the virus, devastated economies, leading to rising unemployment rates, falling consumer activity, and stifled growth (Lee, 2020).

To study how the onset of this crisis affected restaurant performance on digital channels, we rely on data from the Uber Eats platform, a digital food delivery platform offered by the ridesharing company Uber. On Uber Eats, consumers can review menus and order food for delivery or takeout from participating restaurants using an application provided by the platform or through a web browser. In exchange for hosting the transaction and connecting consumers to restaurants, Uber Eats collects a commission on the orders placed on the platform from restaurants and collects delivery charges from customers.

We use order-level data to examine how restaurant demand and performance on the Uber Eats platform changes following the shutdown. Our sample consists of activity on all “Small or Medium Business” (SMB) restaurants, defined as restaurant chains with 50 or fewer locations on the Uber Eats platform, across five major US cities (New York City, San Francisco, Atlanta, Miami, and Dallas) from February 1 to May 1, 2020. A vast majority of these restaurants (over 90% of the SMBs in our sample) have just a single location.

To identify the effect of the closure of dine-in restaurants on restaurant performance on the Uber Eats platform, we take advantage of the enactment of shelter-in-place guidance in each of our five sample cities. For each city, we define a "pre-lockdown" and "post-lockdown" period depending on the date the city enacted shelter-in-place guidance (for all cities, this occurred in mid-March 2020). For example, for New York City, the pre-shutdown period comprises the days February 1 through March 16, and the post-lockdown period comprises the days March 17 through May 1.[7]

We measure restaurant demand and performance using the daily count of orders a restaurant receives.[8] For data anonymity purposes and to ease interpretation of coefficients, order counts at the restaurant-day level are scaled by the pre-period mean count of daily orders across all restaurants within the city. This scaling allows us to interpret changes in levels and coefficients as percentage changes in daily orders relative to pre-period activity levels within the city.

In an ideal natural experiment, we would have a set of control cities that were unaffected by the pandemic.[9] Unfortunately, the pandemic affected all major cities worldwide, leaving no appropriate sample of control cities and limiting our ability to make causal inferences. Nevertheless, even limited to comparing within-city changes pre-lockdown vs. post-lockdown, we believe that the exogenous nature of the pandemic provides insights into how a change in the availability of a traditional channels affects supply and demand through alternative digital channels.

We first provide model-free evidence aligned with the demand-side and supply-side shocks discussed in the introductory section. In Figure 1, we document that the imposition of shelter-in-place orders elicited dramatic changes in consumer behavior on alternative distribution channels. Figure 1 shows how consumer sessions with demand intent have increased post-shutdown across our five sample cities, with an increase in average daily consumer activity that ranges from 25% in Miami to nearly 75% in San Francisco.

[7] Appendix Table A1 summarizes the dates used to define the pre- and post-lockdown periods for each city.
[8] Because of the proprietary nature of the Uber Eats data, we are limited in the outcome measures we can consider at part of this research study, and do not have access to restaurant revenues or order sizes.
[9] For example, if such a set of control cities existed, we could use a difference-in-differences identification strategy to evaluate the causal impact of restaurant closure by comparing trends from the pre-period to the post-period for treatment vs. control cities.

We next turn to examining how consumption changed pre- and post-intervention. As illustrated in Figure 2, following the lockdown, all five cities experienced an increase in the total number of Uber Eats orders placed across all restaurants. The average total number of orders per day was significantly higher in the post-lockdown period across all cities except New York City, with the highest increase in San Francisco (51.9%, $p < 0.01$) and the lowest in New York City (4.1%, $p = 0.13$). What is especially interesting is that these increases occurred despite widespread restaurant shutdowns and cutbacks on operating hours. Many restaurants shuttered entirely, either temporarily or permanently, and of those that did not, many cut back on the hours of operation because of the dramatic decrease in on-site dining activity. As illustrated by Figure 3, following the lockdown, all five cities witnessed a substantial reduction in both the number of restaurants open for business on the platform (Panel A) and the average number of supply hours (Panel B).[10]

The decrease in the number of restaurants open for delivery was largest in New York City (38.1%, $p<0.01$) and smallest in San Francisco (7.6%, $p<0.01$). The decrease in the number of supply hours from restaurants that remained open was fairly consistent across cities (ranging from 6.6% to 9.1%). Thus, the net drop in supply is quite profound across cities, and most dramatic in New York City, where total daily supply hours post-shutdown was, on average, barely half the pre-shutdown level. There are many factors that could have caused this precipitous drop, including restaurants ceasing operations (either temporarily or permanently), and those that remain open for take-out and delivery cutting back on operating hours because of the loss of dine-in customers. A comparison between Figure 3, Panel A and Figure 3, Panel B indicates that both these factors are at play. In New York City, the supply squeeze is driven largely by restaurants closing down, while in San Francisco, cutbacks in operating hours accounts for most of the decline in supply.

The simultaneous increases in demand and decreases in supply have dramatically raised the rate at which active restaurants are receiving and fulfilling orders post-pandemic. As illustrated in Figure 4, order velocity (number of orders fulfilled per available supply hour) increased dramatically across all five cities. The velocity increases are most dramatic in New York City

[10] A restaurant offering supply hours has indicated to the Uber Eats platform at some point during the day that it was available to take orders. We quantify the windows of time that a restaurant indicates availability in this manner by measuring, for each restaurant on each day, its number of supply hours.

and Dallas, where on average, restaurants that were still operating post-lockdown more than doubled the number of orders they are fulfilling per available hour but are by no means small in other cities: nearly doubling in San Francisco, 74% higher in Miami and 71% higher in Atlanta.

Finally, we investigate the overall relationship between total supply and demand on the platform, that is, the number of restaurants offering supply in a city on any given day, and the total number of orders placed in that city on that day. This is summarized in Figure 5. Not surprisingly, an increase in supply is corelated with a net expansion in demand. While this is clearly positive for the platform, the impacts of supply expansion on the providers are not immediately clear, and we explore its competitive effects towards the end of Section 4.

3. MODEL AND RESULTS

Our model-free analysis reveals an increase in total transaction activity coupled with a sharp decline in supply. The analysis that follows aims to better understand restaurant-level impacts, towards unpacking the effects that the availability of the digital channel has on SMB restaurants. We quantify this impact by focusing on one key dependent variable – *the daily number of orders received by a restaurant.* While acknowledging that daily revenue would have been an informative metric, confidentiality concerns precluded the analysis of this measure.

3.1 Baseline model: Impact of lockdown on digital orders

Our first model assumes the following form:

$$Y_{it} = \beta_1 Post_{it} + Restaurant\ FE_i + Day\ of\ Week\ FE_t + \varepsilon \qquad (1)$$

In this equation, *i* indexes the restaurant and *t* indexes the date. *Y* is the count of orders a restaurant receives in a day, our dependent variable, and *Post* is the main independent variable which indicates whether the city has enacted a shelter-in-place order on a given day. *Post* is equal to zero on all pre-lockdown days and is equal to one in all post-lockdown days. Our period of analysis does not include any dates when lockdown orders previously imposed have been lifted. To account for restaurant-specific heterogeneity that may drive our result (including restaurant popularity, cuisine, and the choice of whether to remain open for delivery following the shelter-in-place order) we include restaurant fixed effects. We also include day-of-week fixed effects to account for cyclical variation in order density.

In Table 1, we present results from the regression analysis examining the effect of the shelter-in-place orders on orders on the Uber Eats platform. In Column 1, the sample includes all restaurants that offered some positive level of supply (availability to take orders) on Uber Eats platform in the pre-lockdown or post- lockdown period. In Column 2, we display results for a sample of all restaurant-days for which a restaurant offers supply on the Uber Eats platform.

In both samples, we find that restaurants receive significantly more orders in the post-period than in the pre-period, even controlling for restaurant and day-of-week fixed effects. In Column 1, in the sample of all restaurants that offered supply in either the pre- or post-period, we find that restaurants on average received 12.5 percent more orders a day in the post-period relative to the pre-period ($p<0.01$). In Column 2, using the sample that only contains restaurant-days for which a restaurant offers supply, this effect is much larger, and we find that restaurants that offer supply on a given day receive 44.6 percent more orders a day in the post-period ($p<0.01$).

The difference in effect size across the two samples is because the sample used in Column 1 continues to include, post-lockdown, restaurants that were active prior to the declaration of shelter-in-place guidance but are inactive in the post-period. Thus, a number of restaurants in this sample have zero daily orders for all or most of the post-lockdown time window. We explore the competitive implications of these supply-side changes later in the paper, and in what follows, focus exclusively on the latter sample, since our primary interest is in restaurant-level impacts.

We next consider heterogeneity in this effect across our five cities. We interact the post-shutdown indicator with a binary variable for each city to calculate a city-specific effect. Our model takes the following form:

$$Y_{it} = \beta_1 Post_{it} + \beta_2 Post_{it} \times \ City_i + Restaurant\ FE_i + Day\ of\ Week\ FE_t + \varepsilon \qquad (2)$$

For this analysis, we focus on restaurants offering supply on a given day, and use the sample comprising only restaurant-days for which a restaurant offers supply on the Uber Eats platform (the same data used in Table 1, Column 2). The results of this analysis are presented in Table 2.

Combining the baseline post-effect with the interaction effect for each city in Table 2 allows us to separately identify how the average count of orders per restaurant changes across cities in the post-period. Figure 6 illustrates these results of Table 2, depicting the city-specific marginal effects within each city during the pre-period. A restaurant in San Francisco that continues to offer supply on the Uber Eats platform following shelter-in-place guidance and was getting 10 orders a day on average prior to March 16 would be, on average, receiving 16 orders a day post-shelter-in-place guidance (the marginal effect is a 61.1 percent increase, significant at $p<0.01$). Similarly, Dallas restaurants that remained open and available on the platform have experienced average increases of 53.5 percent and NYC restaurants experienced an effect of about 47.5 percent. Restaurants in Miami have seen the smallest increase (23.2 percent); however, the measured effect is statistically and economically significant (at $p<0.01$) across all cities.

The changes we document in Uber Eats ordering activity may be due to several reasons. The absence of dine-in options may shift demand towards the online channel; variability in the availability of groceries and fears of going to a grocery store may induce consumers to order in rather than cook themselves. In contrast, an increase in the hours people have been spending at home coupled with health concerns associated with food prepared and delivered by people outside their homes could induce an increased propensity and ability to prepare one's own meals; the lack of availability from one's favorite restaurants on the platform could add to this negative demand effect. Our evidence indicates that, in the aggregate, these and other negative demand effects are significantly outweighed by the positive.

3.2 Supply squeeze and competitive effects

The changes in restaurant supply on the platform is likely to influence whether and how a restaurant experiences the demand shock caused by the current pandemic. Restaurants may see particularly large increases in demand and orders if their direct competitors are unable to stay open or provide less supply.

We investigate how a contraction in competitor supply on a digital platform, such as the one witnessed in our empirical setting, affects demand for peers, and analyze how restaurant supply hours and competitive conditions influence the effect of the COVID-19 induced demand shock. To assess the potential moderating effect of competition in determining whether and how the closure of dine-in restaurants affects restaurant performance eon the Uber Eats platform, we require a measure of competition.

We construct three measures of competition using consumer-level data from Uber Eats. The first measure defines each restaurant's competitive set as the other restaurants within the same primary cuisine categorization within the city that provide supply on the Uber Eats platform at some time between February 1 and May 1, 2020. For this measure, the competition index is the percentage of restaurants within a category offering supply on a given day. A higher value in this measure suggests that a consumer would have more options on the Uber Eats platform to choose from within that cuisine category. The second measure is similar but constructed as the percentage of restaurants within a ZIP code offering supply on a given day.

Our third measure of competition is more novel. We use order-level data from Uber Eats in the year prior to the beginning of our sample period (the training period February 2019 through January 2020) to construct a bipartite consumer-restaurant graph that draws on analogous measures of product complementarity from the collaborative filtering literature. Let x_{ij} be the number of orders customer *i* has placed at restaurant *j* during the training period and let $r_j = \sum_{i=1}^{m} x_{ij}$ and $c_i = \sum_{j=1}^{n} x_{ij}$ be the number of orders received by restaurant *j* and placed by customer *i* respectively. Then the competitive intensity of restaurant *b* on restaurant *a* is the sum, across all customers of restaurant *a*, the likelihood each customer orders from restaurant *b* weighted by the importance of the customer to restaurant *a*, or

$$CompetitiveIntensity(a,b) = \sum_{i=1}^{n} \frac{x_{ia}x_{ib}}{r_a c_i}.$$

Breaking this measure down into its component parts, the "importance" of customer *i* to restaurant *a* is simply the count of orders from customer *i* to restaurant *a* divided by the total count of orders received by restaurant *a* during the sample period ($\frac{x_{ia}}{r_a}$). Correspondingly, the likelihood that customer *i* orders from restaurant *b* as the count of orders from customer *i* to restaurant *b* divided by the total count of orders made by customer *i* during the sample time period ($\frac{x_{ib}}{c_i}$). Summing this product across all overlapping customers generates the dyad-level competitive intensity score for the pair (*a*, *b*). The level of competition that a restaurant faces on a given day is thus simply the competitive intensity scores for each dyad the restaurant is in for which the competing restaurant is open on that day.[11]

We use a model of the following form to estimate the role of competition in determining the effect of the COVID shock on restaurant performance:

[11] Appendix Figure A2 displays the distribution of the three competitive indices pooled across all sample cities.

$$Y_{it} = \beta_1 Post_{it} + \beta_2 Competition\ Index_{it} + \ \beta_3 Post_{it} \times \ Competition\ Index_{it} + Restaurant\ FE_i + Day\ of\ Week\ FE_t + \varepsilon \qquad (4)$$

By interacting each of our measures of competition with the post indicator variable, we identify how the level of competition on a given day moderates the effect of dine-in restaurant closure on restaurant performance on the Uber Eats. Comparing the effect of our competition indicator in the pre- vs. post-period, we identify whether and how the relative supply of peer restaurants affects the increase in restaurant demand following the shock. Our results are presented in Table 3 below.

Columns 1, 3, and 5 indicate that predictably, competition has a negative effect in both the pre- and post-period and provides insight into the which measures most accurately reflect competition. For example, relative to the cuisine measure or the network measure, an equivalent increase in the ZIP measure of competition has a smaller negative effect on daily orders received on the Uber Eats platform, suggesting that competition may be more intense at the cuisine-level or across overlapping consumers than at the narrow geographic level.

Considering the interaction between the post-indicator and the measures of competition reveals how competition changes following the imposition of the shelter-in-place orders. While it appears that there is no significant difference in the ZIP measure of competition pre- and post-shock, the effects of competition, as measured by the cuisine and network measure, are stronger in the post-period across all measures considered. Column 2 suggests that a ten percent increase in the number of restaurants open within a cuisine category is associated with a 6.3% decrease in the count of orders a restaurant receives in the pre-period (at $p<0.01$), while the equivalent increase in the number of restaurants open within a cuisine category is associated with an 8.6% decrease in the count of orders a restaurant receives (at $p<0.01$). The difference is starker with the network-based measure, as our results suggest that this measure had no meaningful relationship with restaurant orders in the pre-period, but post-lockdown, a ten percent increase in the network measure is associated with 9.1% fewer orders (at $p<0.01$). It is possible that, pre-lockdowns, the presence of similar restaurants with overlapping customers may have generated positive spillovers through indirect network effects (i.e., consumers are attracted to the platform by one restaurant and then explore and discover other related restaurants) (Katz and Shapiro, 1985; Rochet and Tirole, 2003; Weyl, 2010), however, following the shock and the resultant increase in demand and consumer activity, such spillovers no longer stimulate sufficient demand to overcome the negative effects of substitution.

These results suggest a tension between what is best for the platform and what is best for providers on the platform. As shown in Figure 5, the more restaurants on the platform, the greater total consumption is. However, as demonstrated in Table 3, more competition on the platform decreases the count of orders each restaurant receives. It is possible that, over a longer period of time, these competitive effects may be offset by indirect network effects if a greater number of providers brings more consumers to the platform. Nevertheless, digital platforms must navigate this tension in attempting to manage both the consumer and supplier-side of the platform, and this represents a promising area for future work.

4. CONCLUSION

As markets continue to rebound from the effects of the pandemic, "business-as-usual" has been transformed. There is likely to be a significant and permanent shift away from in-person commerce and towards digital interaction. This is not limited to the restaurant industry –apparel and accessories stores experienced a year-over-year decline of 89.3% in April 2020, which while understandable given shelter-in-place orders and pandemic-related fears, is staggering, perhaps the biggest YoY decline in any sector ever, and an inflection point that signals the future dominance of ecommerce in this sector (Tappe and Meyersohn, 2020).

While the pandemic caused many restaurants to close their doors for good, those that survive will be the ones which were able to best leverage alternative distribution channels. Because of social distancing, enhanced cleaning protocols, and consumer hesitancy, the costs of dine-in will increase significantly, making a digital channel all but essential for restaurant survival. The connection between platform-sourced demand and survival will be indelible, likely leading the survivors to double down on digital, seeing it as a critical source of resilience.

All of these factors point to the heightened importance of platforms like Uber Eats in the economy of the future. Our findings provide insight into the details and dynamics of the role that such platforms play in mitigating the adverse effects of negative economic shocks, underscoring the risks associated with policy that may curtail their growth or reach, while also shedding new light on the different economic factors at play when a business sells through a platform.

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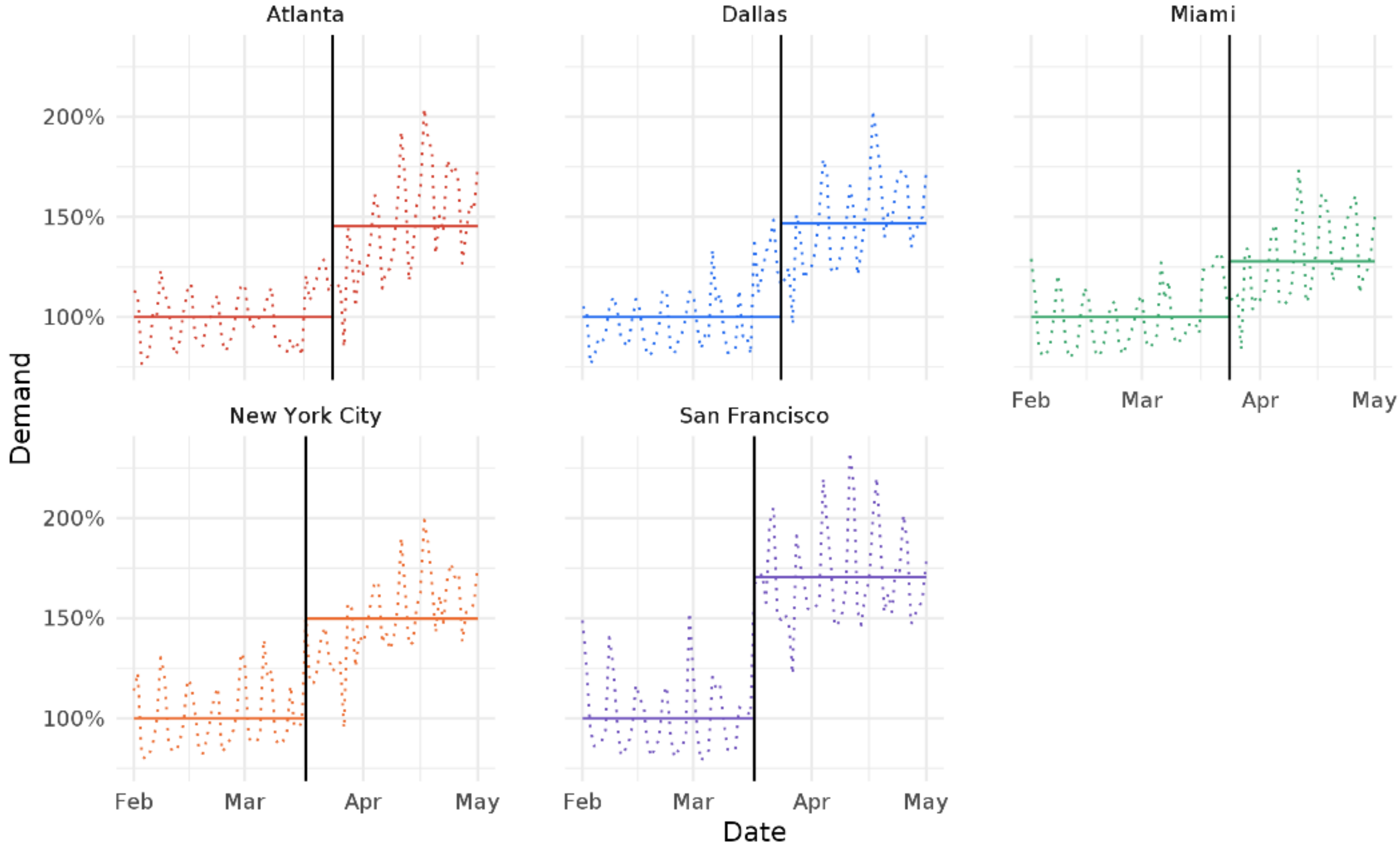
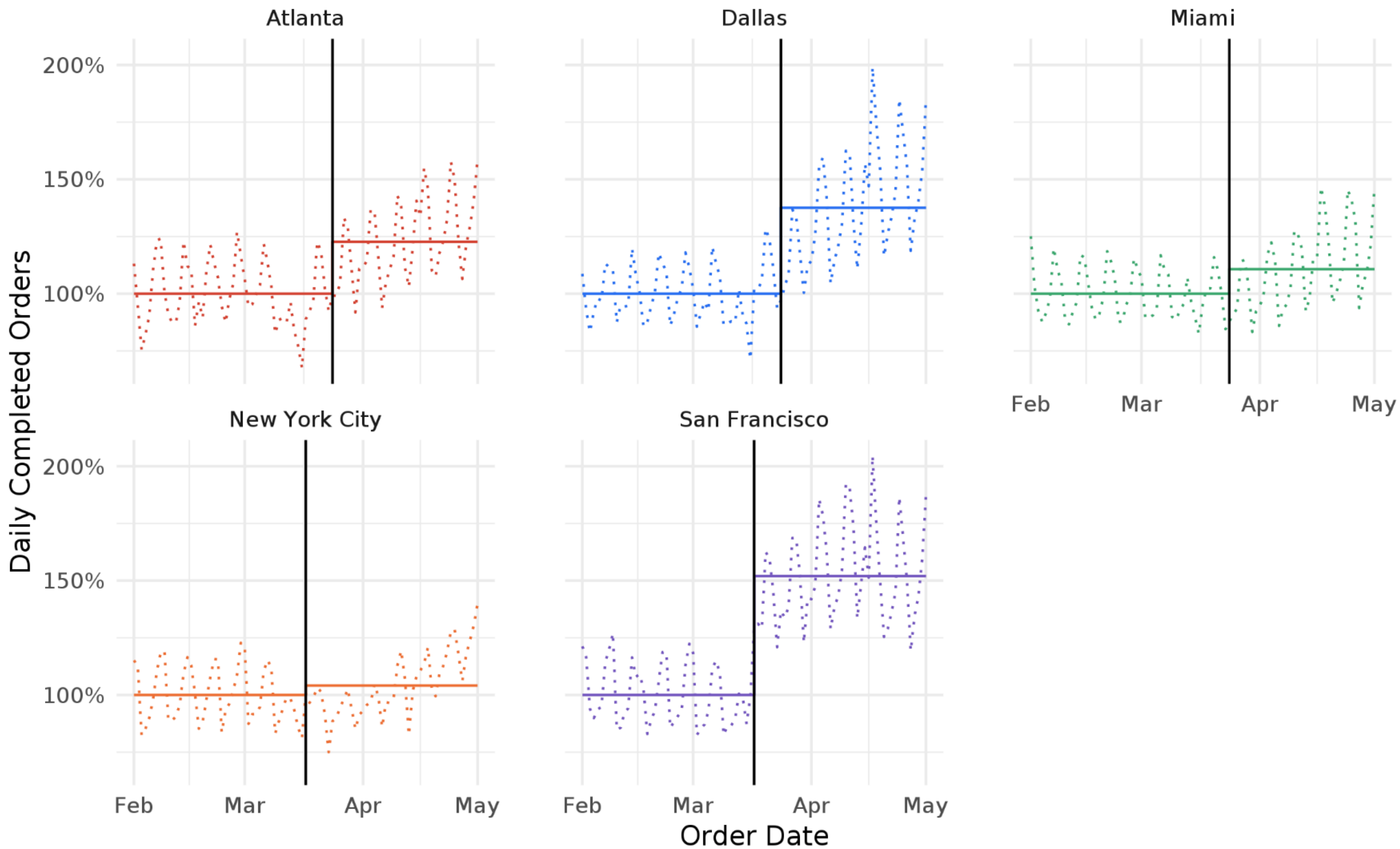
Figure 1: Changes in Consumer Sessions with Demand Intent in Response to the COVID-19 Pandemic on the Uber Eats Platform



Note: In Panel A, the dotted curves plot the daily number of consumer sessions with demand intent between February 1 and May 1 across our five cities, normalized such that the average pre-lockdown value equal to 1. The vertical line represents the day on which the shelter-in-place guidance was issued. The solid horizontal lines depict the average daily number of consumer sessions with demand intent in the pre-lockdown and post-lockdown time windows.

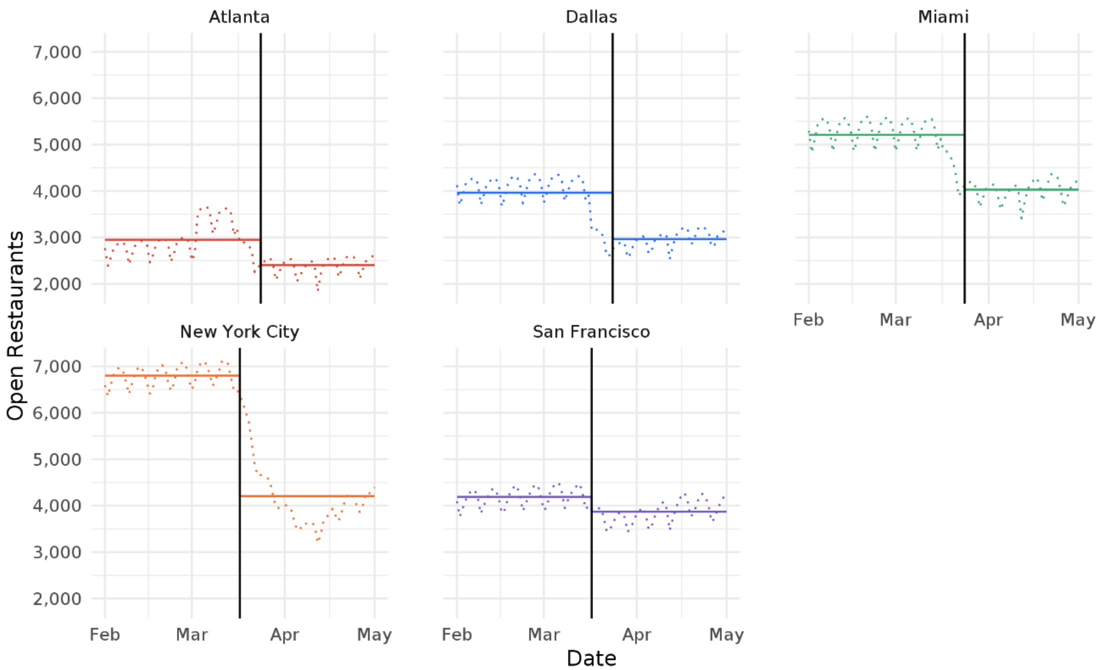
Figure 2: Changes in Total Daily Orders on the Uber Eats Platform in Response to the COVID-19 Pandemic



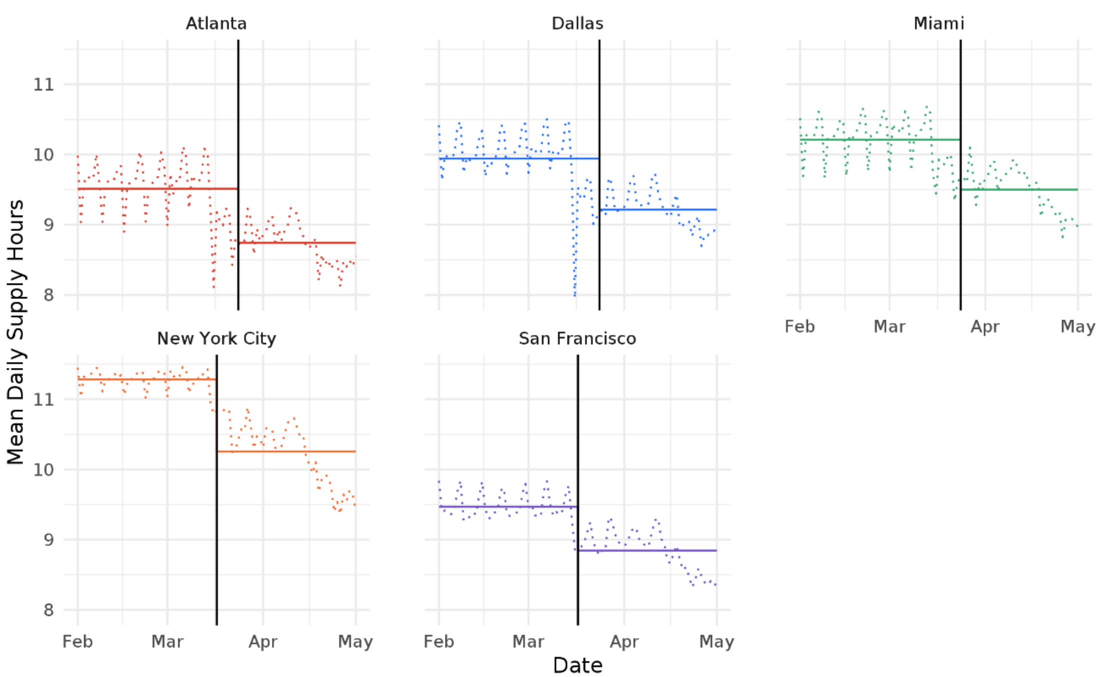
Note: The figure displays the daily number of orders fulfilled by restaurants between February 1 and May 1 across our five cities. The vertical line represents the day on which the shelter-in-place guidance was issued. The solid horizontal lines depict the average daily number of completed orders in the pre-lockdown and post-lockdown time windows.

Figure 3: Supply-Side Response to COVID-19 Pandemic on the Uber Eats Platform

A. Number of Open Restaurants.

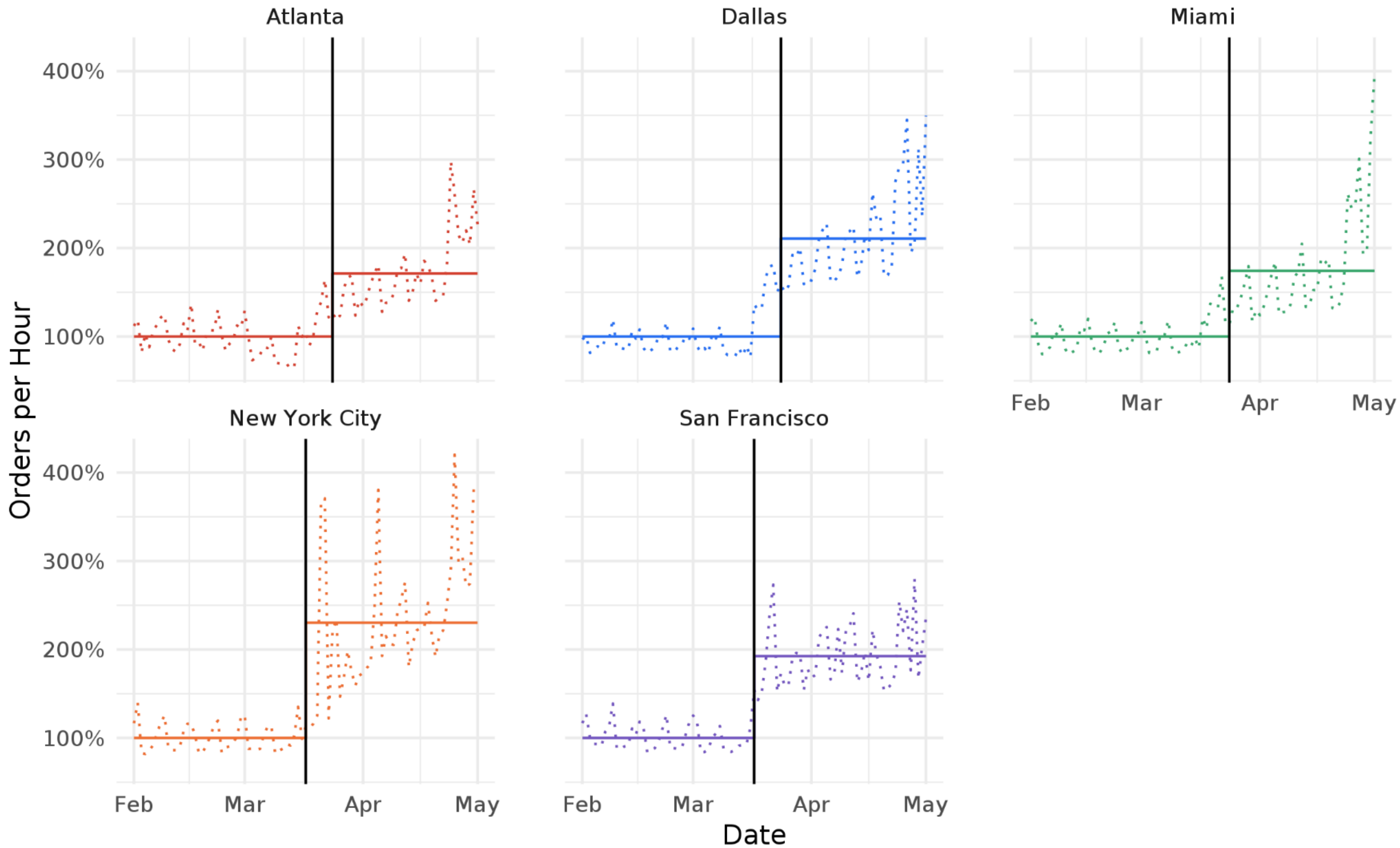


B. Average Daily Supply Hours for Open Restaurants.



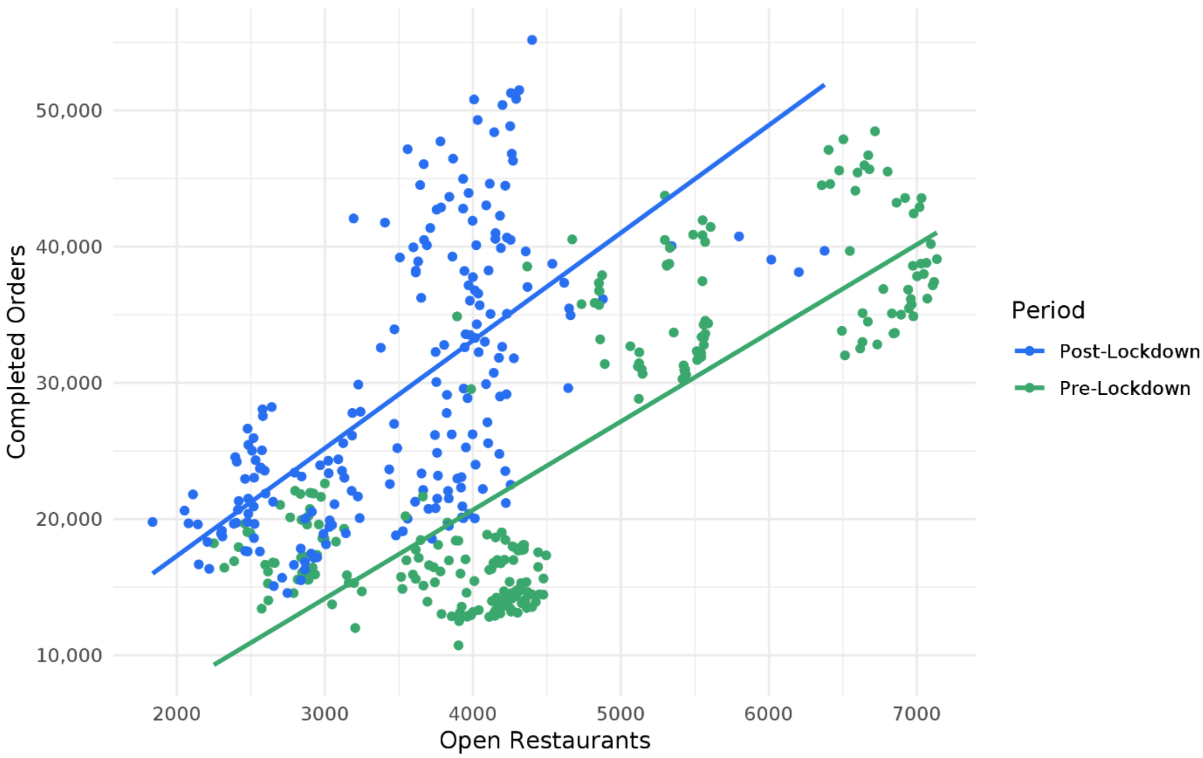
Note: In Panel A, the dotted curves plot the average number of restaurants that offer at least one hour of supply on the Uber Eats platform on any given day. In Panel B, the dotted curves plot the average number of daily supply hours per restaurant, only counting restaurants that offer supply on the Uber Eats platform on any given day. The vertical line represents the day on which the shelter-in-place guidance was issued. In both charts, the solid horizontal lines depict the average in the pre-lockdown and post-lockdown windows.

Figure 4: Changes in Order Velocity on the Uber Eats Platform in Response to the COVID-19 Pandemic



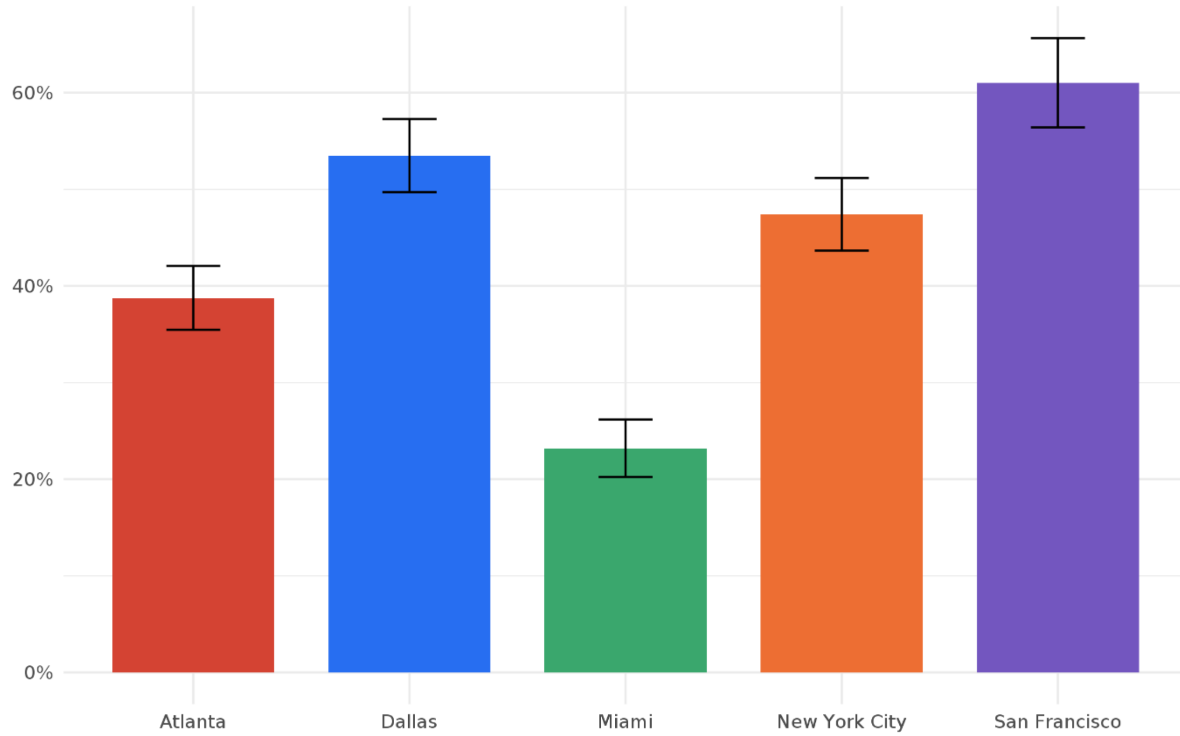
Note: The dotted curves plot the daily number of orders/supply hour (normalized velocity) fulfilled by restaurants between February 1 and May 1 across our five cities, normalized in a way that makes the average pre-lockdown value equal to 1. The vertical line represents the day on which the shelter-in-place guidance was issued. The solid horizontal lines depict the average normalized velocity in the pre-lockdown and post-lockdown time windows.

Figure 5: Open Restaurants and Completed Orders on the Uber Eats Platform



Note: The dots plot the relationship between the count of restaurants offering supply in a city on a given day and the total count of completed orders within the city on that same day. The solid lines plot a simple linear relationship between restaurant supply and completed orders at the city-day level.

Figure 6: City-Specific Impact of Shelter-in-Place Guidance on Daily Orders on the Uber Eats Platform



Note: The figure displays a bar chart displaying the city-specific marginal effect of shelter-in-place guidance on daily orders for restaurants offering supply on a given day. Each bar depicts, for the respective city, the percentage increase in average daily orders per restaurant in the post-lockdown period, relative to the average number of orders received by restaurants in that city during the pre-lockdown period. The error bars depict the 95% confidence interval. Estimates are derived from the regression results presented in Table 2.

Table 1: Regression Estimate of the Change in Daily Restaurant Orders on the Uber Eats Platform in Response to the COVID-19 Pandemic

Dependent Variable:	Daily orders	
Model:	(1)	(2)
Post	0.125***	0.446***
	(0.008)	(0.009)
Restaurant fixed effects	Yes	Yes
Day of week fixed effects	Yes	Yes
Observations	2,727,709	1,862,748
R^2	0.739	0.794
Adjusted R^2	0.736	0.790

One-way (Restaurant) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table presents regression results that assess the impact of shutdown orders on daily order counts on the Uber Eats platform. The variable *Post* takes the value 0 for all observations February 1 through the declaration of shelter-in-place guidance in a given city, and the value 1 for all observations following the declaration of shelter-in-place guidance through May 1. The data set in Column 1 is a balanced panel consisting of all restaurants that offered supply on at least one day between February 1 through May 1. The data set in Column 2 is an unbalanced panel consisting of only those restaurant-days for which the restaurant offered positive supply on that day. The dependent variable is scaled by the within-city pre-period mean. Standard errors are clustered at the restaurant-level.

Table 2: Regression Estimate of the City-Specific Change in Daily Restaurant Orders on the Uber Eats Platform in Response to the COVID-19 Pandemic

Dependent Variable:	Daily orders	
Model:	(1)	(2)
Post	0.120***	0.388***
	(0.016)	(0.017)
Post × Dallas	0.091***	0.147***
	(0.024)	(0.026)
Post × Miami	-0.068***	-0.156***
	(0.021)	(0.023)
Post × New York City	-0.142***	0.087***
	(0.023)	(0.026)
Post × San Francisco	0.255***	0.223***
	(0.027)	(0.029)
Restaurant fixed effects	Yes	Yes
Day of week fixed effects	Yes	Yes
Observations	2,727,709	1,862,748
R^2	0.740	0.795
Adjusted R^2	0.737	0.791

One-way (Restaurant) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table presents regression results that assess the variation across cities in the impact of shutdown orders on daily order counts on the Uber Eats platform. This analysis is analogous to Table 1, except the *Post* variable is interacted with an indicator variable for each city. The data set is an unbalanced panel consisting of only those restaurant-days for which the restaurant offered positive supply on that day. The dependent variable is scaled by the within-city pre-period mean. Standard errors are clustered at the restaurant-level.

Table 3: Regression Estimate of the Effect of Competition on Daily Orders on the Uber Eats Platform in Response to the COVID-19 Pandemic

Dependent Variable:	Daily orders					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.320***	0.439***	0.403***	0.370***	0.373***	0.952***
	(0.014)	(0.031)	(0.011)	(0.036)	(0.013)	(0.051)
Cuisine measure	-0.731***	-0.634***				
	(0.078)	(0.075)				
Post × Cuisine measure		-0.227***				
		(0.055)				
ZIP measure			-0.272***	-0.306***		
			(0.049)	(0.055)		
Post × ZIP measure				0.071		
				(0.075)		
Network measure					-0.558***	-0.013
					(0.081)	(0.084)
Post × Network measure						-0.910***
						(0.079)
Restaurant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,862,748	1,862,748	1,862,748	1,862,748	1,671,821	1,671,821
R^2	0.794	0.794	0.794	0.794	0.796	0.796
Adjusted R^2	0.790	0.790	0.790	0.790	0.793	0.793

One-way (Restaurant) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The table presents regression results that assess the variation across cities in the impact of shutdown orders on daily order counts on the Uber Eats platform. This analysis is analogous to Table 1, except the *Post* variable is interacted with constructed measures of competition. The data set is an unbalanced panel consisting of only those restaurant-days for which the restaurant offered positive supply on that day. The dependent variable is scaled by the within-city pre-period mean. Standard errors are clustered at the restaurant-level.