The Impact of Online Food Delivery Services on Restaurant Sales

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Abstract

The rapid growth of online food delivery services has disrupted the traditionally offline restaurant industry. This study presents empirical evidence on the crowding-out effects and market expansions induced by the staggered entry of online food delivery services. Difference-in-differences methodology reveals that 30-50 cents of every dollar spent on online food delivery services are incremental, while the rest is drawn away from brick-and-mortar sales. These findings are statistically significant at the zip code-level and are heterogeneous across different types of consumption, suggesting that convenience and pre-existing spending habits drive the level of substitution. Conducting analyses on a year-by-year basis suggests that there is an increasing level of cannibalization of brick-and-mortar restaurant sales. Back-of-the-envelope calculations show an increase in restaurants' revenues but a decrease in profitability.

Keywords: E-commerce, market expansion, sales cannibalization

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"Online delivery is surging, and eating in is the new dining out. Online commerce reduced traffic in brick-and-mortar stores, which this year are closing at a record-setting pace... Meal-delivery companies are a symbol of what might be the most powerful force in business today: convenience maximalism."

Derek Thompson, *The Atlantic* (2019)

1 Introduction

The meteoric growth of e-commerce makes it an ever-important area to study. Even in traditional industries, well-established offline firms have adopted new online sales channels that aim to increase their revenue. This has led to the hybridization of strictly brick-and-mortar stores, which now operate both online and offline. In fact, by 2012, more than 80 percent of U.S. retailers sold merchandise through both online and offline channels (Wang, Song, and Yang 2012). One of the most prolific applications of this recent hybridization is in the restaurant industry, with the emergence of online food delivery services. Delivery transactions made up six percent of total US restaurant sales in 2017 and are estimated to reach 40 percent of all restaurant sales by 2020 (Morgan Stanley Research 2017).[1] However, the extent to which these online sales are incremental—causing overall restaurant sales to increase—or, alternatively, drawn away from brick-and-mortar sales, has not been quantified.

Online food delivery is a prime example of e-commerce disrupting a traditional market. A flood of new food delivery firms has caused rapid growth in the total number of transactions and revenue for the nascent industry. Although online food delivery services provide extra channels for potential revenue, they also create the risk of cannibalization in which brick-and-mortar sales actually suffer because consumers who purchase in-store have transitioned to mostly online purchasing behavior. The purpose of this study is to determine the effects that the entry of these firms—and subsequent hybridization—has had on restaurant sales

[1]The COVID-19 pandemic may further accelerate this trend because in-person dining has essentially been shut down.

by quantifying the levels of substitution between in-person restaurant sales and online food delivery services.

The staggered deployment and expansion of online food delivery services across time and space provides an opportunity to estimate these effects and how they vary across locations and over time. In order to do so, I use the universe of Visa Inc.'s individual-level credit and debit transactional data. Each observation in the main dataset is an individual transaction between a business (the merchant) and a consumer (a cardholder). On the merchant side, the name, zip code, and category of the business are recorded. On the cardholder side, only the anonymized card number is visible. Other variables of interest include the transaction amount and a record of how the purchase was conducted (a physical card swipe, online transaction, phone charge, etc.). The data encapsulates all businesses at which cardholders use their Visa cards. In order to maintain a sample that is useful for the analysis, the data is restricted to purchases that occurred at restaurants in the United States from 2014 through 2017. Cardholder location and family status are imputed based on transactional history. The analysis explores heterogeneity along these dimensions, as well as other factors of time and space.

The primary empirical specification is a standard differences-in-differences with a continuous treatment variable. I regress total dollars-per-card—brick-and-mortar and online food delivery service sales—spent at restaurants on dollars-per-card spent on online food delivery services with month and zip code fixed effects in order to quantify the level cannibalization of restaurant sales. If the two are uncorrelated, this suggests that every dollar spent on online food delivery service is cannibalized; if the two are perfectly correlated, this suggests that online food delivery services are providing purely incremental sales to restaurants. More specifically, the coefficient on online sales shows the fraction of each dollar spent on online food delivery services that is new; the remainder is drawn away from brick-and-mortar sales.

I find that roughly half of each dollar spent on online food delivery services is new, whereas the remaining half is converted from in-person restaurant sales. This suggests that online food delivery services provide modest incremental sales, but also draw away from traditional sales. Stratifying the regression by the time of transaction shows that while each dollar spent on online food delivery services during lunch, dinner, different seasons, and the work week provide some additional sales, online food delivery sales during the weekend are mostly cannibalized from brick-and-mortar sales. The differences in these estimates suggest that convenience is an important factor in drawing consumers to online food delivery services. Considering time constraints during the week, the ease of online food delivery services may be driving the higher level of substitution between online and offline channels.

Separating zip codes into quartiles of average monthly restaurant expenditure shows that the lower quartiles substitute only 10 percent every dollar spent on online food delivery services, whereas the higher quartiles substitute up to half of every dollar spent on online food delivery services. This suggests that online food delivery services are drawing in those who typically do not spend much at restaurants. The distinction of urban and rural regions shows that rural areas provide almost completely new restaurant sales via online food delivery services; the region of the U.S.—northern or southern states—has little effect on the levels of substitution. Finally, conducting a year-over-year analysis shows that the additional sales provided by online food delivery services are decreasing over time. This suggests that there is incremental cannibalization of brick-and-mortar restaurant sales as exposure to online food delivery services increases. Further, back-of-the-envelope calculations show that restaurants' revenues are increasing but their profitability is decreasing.

There are many descriptive studies that document the growth of online food delivery services and the characteristics of the customers that use them (Morgan Stanley Research 2017; Technomic Food Trends 2018; Wirth 2018; Zion, Spangler, and Hollmann 2018). However, these studies rely on self-reported qualitative surveys that were sent out to a few thousand individuals, which could potentially lead to selection bias, reporting inaccuracies, and attrition rates over time. The analysis presented in this study quantifies cannibalization of traditional restaurant sales by online food delivery services using a large, representative network of transactions. This not only contributes to a growing literature on substitution between online and offline sales channels by examining a new and growing industry, but also provides some of the first empirical evidence on the impact of online food delivery services.

Although this study focuses on online food delivery services, the results could potentially be extrapolated to different markets. Other traditional markets have many confounding factors such as a less transparent firm-entry pattern, which leads to difficulty in quantifying the effects of e-commerce. Restaurants and online food delivery services, however, lend themselves well to studying these effects. While there might be other outside factors in different industries that impact the causal effects of e-commerce, the lessons derived here are likely similar elsewhere.

The rest of the paper is organized as follows. In Section 2 and Section 3, I provide background on the evolution of online food delivery services and literature related to online-offline substitution. Section 4 introduces the data, the construction of key variables, and relevant summary statistics. Section 5 and Section 6 describe the empirical strategy and results, respectively. Section 7 concludes briefly.

2 Background

Online food delivery services have been around for quite some time. Several chain restaurants created websites to order take-out, but these services were limited to within the chain's own restaurants.[2] Individual restaurants followed suit, creating their own websites for delivery. Even grocery stores began offering online delivery in the early 21st century (Pozzi 2012; Relihan 2017). However, generalized online food delivery services that offer delivery from many different restaurants have only become popular in the past decade—and they have done so rapidly.

By 2018, the online food delivery service industry had an estimated $82 billion in gross

[2] "PizzaNet," Pizza Hut's original online ordering destination, accepted and delivered the first online food delivery in 1994.

revenue, and accounted for 6 percent of the restaurant market in 2020 (Frost and Sullivan 2018; Morgan Stanley Research 2020). These firms are backed by revenue growth in excess of 14 percent over the past four years, and are on track to double their market share by 2025 (Morgan Stanley Research 2020). The rapid expansion of these firms has even influenced some restaurants to change their entire layouts, and migrate to a "delivery only" model (Bond 2019). It is clear that the restaurant market is evolving.

The first online food delivery firm, Grubhub, was founded in 2004 with the goal of replacing all paper menus with a single website. Since then, Grubhub has transitioned to connecting delivery drivers from those restaurants in order to deliver to customers. Postmates, Doordash, and other firms operate slightly differently from Grubhub. These newer firms—which were founded in 2011 and 2013, respectively—provide menus from restaurants as well as contracting out delivery drivers, much like Uber or Lyft.[3] These firms adopted very similar growth strategies in which they start in select cities and expand to others with their success.[4]

Consumers that use online food delivery services also have a few empirically quantified characteristics. Delivery is ordered to the consumer's home 86 percent of the time, and 74 percent of sales occur on weekends (Hirschberger et al. 2017). Further, in 2017, 43 percent of individuals who ordered with online food delivery services say that it replaced an in-person meal at a restaurant. This figure increased from 38 percent just the year before, suggesting that there is incremental cannibalization with the introduction of online channels (Morgan Stanley 2017).

Online food delivery services often state that they are providing supplementary sales to restaurants. In fact, a survey of several thousand restaurateurs found that offering online delivery has generated additional sales for 60 percent of restaurant operators (Technomic Food Trends 2018). While online food delivery services claim, and actually do, provide incremental sales, the profitability of restaurants is declining as online delivery increases

[3] This background information on specific firms was found on company websites.
[4] The heterogeneity over time and location is key to the analysis in this study.

(Dunn 2018; Thompson 2019). This is mostly due to high fees that online food delivery services charge, not only as service and delivery charges to the consumer, but also to the restaurant. Most online food delivery services charge the restaurant between 20-30 percent of each purchase. Online delivery often represents a large bulk of business for restaurants, so it's not an option to cut online sales channels.

In the age of a pandemic, the demand for online food delivery services sales is spiking. In fact, in China, online food delivery service orders surged 20 percent during January alone; firms such as Doordash have even started reducing or eliminating their fees in response to the surge that is beginning in the United States (Keshner 2020). It is expected that consumers will continue to increase their usage of online food delivery services so long as there are stay-at-home orders and sit-down restaurants remain closed, although this likely will not completely replace pre-pandemic restaurant spending. As COVID-19 continues to impact the United States, the demand for non-contact food delivery services will likely follow the example of China and expand greatly. Understanding consumer behavior as it relates to online food delivery services is essential in this rapidly changing environment.

3 Literature Review

Recent studies have described a "retail apocalypse" in which e-commerce has forced brick-and-mortar retail establishments without online channels to shut down across the nation. However, physical stores are not quite finished. The "bricks-and-clicks" hybrid model has become more and more popular—and this trend has not been limited to just retail stores (Hortaçsu and Syverson 2015).[5]

This study seeks to quantify potential crowding-out effects and market expansions that have occurred due to the entry of online food delivery services and subsequent hybridization of restaurants. "Crowding-out" refers to sales that usually occur in brick-and-mortar stores that are now happening via other channels. Market expansions refer to new sales that

[5] A thorough review of studies on e-commerce can be found in Lieber and Syverson (2012).

are generated by creating an online channel for purchases. Although opening new online channels could potentially increase restaurant revenues and cause overall market expansion, new channels also allow for cannibalization of offline sales, i.e. crowding-out. Firms face a similar trade-off when introducing new products or opening a new store (Shaked and Sutton 1990; Holmes 2011; Mitsukuma 2012). Consumers that would typically purchase meals in-person are now ordering take-out with online food delivery services.

A rich academic literature describes the effects of opening new sales channels, especially relating to e-commerce. There is a particular focus on the investigation of potential market expansions and substitution effects that could be introduced with online channels in traditional markets. These studies have found significant substitution effects across different industries, such as groceries, newspapers, and consumer electronics (Duch-Brown et al. 2017; Wang, Song, and Yang 2013; Pozzi 2013; Gentzkow 2007). The majority of studies in this literature describe the effects of Internet-based substitutes for traditional goods and services from the consumers' perspective. Electronic goods and computers are found to have relatively sensitive prices between the online and offline purchasing channels (Goolsbee 2001; Prince, 2007). Online presence of advertisements on Craigslist lowered those found in newspapers and even reduced home and rental vacancy rates (Kroft and Pope 2014). However, in the context of restaurants, the impact of introducing online food delivery services is not as well understood.

There is limited empirical evidence on the impact of adding an online sales channel to a traditional industry from the firms' perspective. In the newspaper industry, the introduction of online articles caused significant substitution effects that greatly reduced the readership of print media (Gentzkow 2007). Grocery store sales are only moderately crowded-out with the introduction of an online channel and their overall revenues increase (Pozzi 2012; Relihan 2017). In fact, it is generally found that including an online sales channel provides significant increases in sales, inventory, and return on investments, while costs decrease in a sample of more than one hundred publicly traded companies (Xia and Zhang 2010).

The literature related specifically to online food delivery services is even more limited. These types of firms have been studied only in very narrow contexts. Survey-based descriptive statistics show what types of consumers use online food delivery services (Yeo, Goh, and Rezaei 2017 2017). Traffic and routing of drivers is studied in order to determine the effects on customer satisfaction (Pigatto et al. 2017). Website quality—estimated by the number of clicks—is quantified, as is the correlation between consumer ratings and brand loyalty (Correa et al. 2019; Ilham 2018). Not only are these studies limited in scope, but they have also been constrained to countries outside of the United States, with the exception of some non-academic survey methodologies. The effects of online food delivery services are not quantified, especially in terms of crowding-out of brick-and-mortar sales.

Crowding-out effects, although well understood in some industries, have not been empirically studied in the context of restaurants. The case of online food delivery services is especially interesting because a third party offers the delivery service, rather than the individual restaurant opening its own specialized online channel. Further, the cannibalization of restaurant sales by online food delivery services has recently become a large point of contention.[6] This study fills a gap in the literature related to online food delivery services and their impacts on restaurants, addressing growing concerns in the restaurant industry, especially in light of COVID-19.

4 Data

4.1 Sources

The analysis leverages a proprietary transaction-level dataset provided by Visa Inc., which covers the universe of credit and debit transactions in the Visa network beginning in 2009 and up to and including 2019. Visa Inc. (NYSE: V) is the world's leader in digital payments.

[6] Elizabeth Dunn describes the case of a restaurant in New York City that is experiencing reduced profitability with increased online food delivery orders due to delivery service fees that are about 20-40 percent of each order (Dunn 2018).

It has a steadily increasing market share of credit card volume, which surpassed 53 percent in 2017, and has maintained a market share of more than 70 percent of debit card volume throughout the sample (Peter 2019).[7] The Visa data contains an annual average of 380 million cards, 35.9 billion transactions, and $1.93 trillion in sales. Of these sales, 55 percent were credit transactions and 45 percent were debit transactions. Visa volume has been steadily increasing over time, from approximately 14 percent of consumption in 2009 to almost 22 percent of consumption in 2017 (Dolfen et al. 2019).

The unit of observation in the underlying data is a transaction between a cardholder and a merchant. The cardholder is the individual who used their Visa card to purchase a good or service, and the merchant is the business that provided that good or service. On the merchant side, a business name, location, and business category are recorded. The location is recorded as a zip code and the business category is the type of the business (e.g., restaurant, toy store, clothing retailer, etc.) recorded by Visa. On the card side, only a unique card identifier is provided. This is the credit or debit card number. The data does not contain information pertaining to the specific goods or services purchased in each transaction, nor does it record the quantity, or price of the items. The sample is completely anonymized, so the name, address, or any other personally identifiable information about the cardholder is not observable, other than what can be inferred given the card's transaction history. Cards that are used by the same person or family are not linked to one another.

Each transaction has a number of observable characteristics that are pertinent to the analysis, other than the cardholder and merchant identifiers. The transaction amount in dollars, date, time, and card type—credit or debit—of transaction are recorded. Further, there are several variables that define the type of transaction that occurred. Each transaction indicates whether or not it occurred in person. Approximately half of the transactions that did not occur in person are broken down into online, mail order, phone order, and recurring transactions; the remaining transactions only record that the card was not present.

[7] The remainder of each of these markets is divided between MasterCard, American Express, and Discover.

4.2 Analysis Sample

The analysis sample uses all transactions that occurred at restaurants—characterized by Visa's merchant category variable—between 2014 and 2017 that pass a series of filters. Transactions that are not located in the United States are not included in the sample. Only completed and processed transactions are included. Further, debit-PIN transactions are excluded because of inconsistent routing practices.[8] Cardholders that made fewer than five purchases at restaurants and spend more than $3,000 dollars per month at restaurants are not included in order to exclude gift cards and corporate cards. Finally, cards that did not transact on online food delivery services are omitted from the sample.

4.3 Variable Construction

The analysis relies on several data constructs that characterize different types of transactions and cardholders. First, the consumer's preferred shopping location is imputed from their transactional history. Recalling that the five-digit zip code of the merchant is available for each offline transaction, the modal zip code of offline transactions in which a card transacts at least 20 times is used to define a cardholder's location. Dolfen et al. (2019) determined the cardholder's preferred shopping location as a latitude-longitude pair given by a transaction-weighted average zip code centroid and found that it is robust to more precise cardholder residential addresses from a large credit rating agency. This lends credibility to the modal zip code estimate, which is a less granular definition of the consumer's location.

In order to characterize transactions as restaurant sales and online food delivery sales, the merchant name, card presence, and merchant category variables are used. In the case that the transaction occurred using online food delivery services, the name of the delivery service is recorded as the merchant name. The transactions that do not have a physical card swipe,

[8] Following the Durbin Amendment in the Dodd-Frank Bill of 2010, payment card networks were no longer able to restrict how merchants routed PIN-based debit transactions. Therefore, after the bill became law in 2012, massive fluctuations appeared in debit-PIN transactions. In order to maintain a sample with consistent routing, only credit and debit-signature transactions are included, which make up the vast majority of the dataset

are listed as restaurant purchases by Visa, and have merchant names that map to the top online food delivery services—Doordash, UberEats, Postmates, Caviar, Grubhub, Seamless, and Delivery.com—are classified as online food delivery service sales. Total restaurant sales are all transactions characterized as restaurant purchases by Visa.

The cardholder's transactional history is also used to separate different types of consumers. In particular, individuals that used cards at children's clothing or toy stores—again, characterized by the merchant business category—at some point between 2014-2017 are identified as cardholders that have young children. If the cardholder does not purchase any goods from these types of stores, they are identified as not having children. Roughly one third of unique cards transact at children's clothing or toy stores at some point.

The time and date of transactions are also used to characterize different types of purchases. The date is used to separate weekday and weekend transactions using the day of the week, and the time of the transaction—which is measured down to the second—is used to separate lunch and dinner transactions. Lunch purchases are defined as those that occur prior to 5 pm, and dinner transactions are those that occur after 5 pm.

The analysis relies on monthly data aggregated up to the zip code level. The transaction total in dollars for restaurants and online food delivery services are recorded, along with the number of distinct cards. The sample is stratified according to the different types of transactions and cardholders delineated above. The main variables of interest for the analysis are measured in dollars-per-card, so the dollar amounts are adjusted accordingly. The sample is augmented by zip code-level characteristics, including voting tendencies defined as the results of the 2016 presidential election, urban-rural characterization based on American Community Survey data, and quartiles of average per-card monthly restaurant expenditure which are generated based on zip code-level average monthly spending at restaurants.

4.4 Summary Statistics

Before describing the main analysis of the study, it is useful to consider some initial summary statistics. First, panels of different types of cardholders and transactions are broken down in order to describe the number of cards and transactions, measured in millions of cards and swipes, as well as total restaurant sales, and online food delivery sales, measured in millions of dollars. These statistics are presented in Table 1.

Table 1: Panel Summary

Panel	**Cards**	**Transactions**	**Restaurant Sales**	**OFD Sales**
Overall	1.47	60.78	5,584.03	381.39
Lunch	1.46	30.67	3,352.44	195.54
Dinner	1.46	30.11	2,231.59	185.85
Weekend	1.47	24.67	1,527.56	109.39
Weekday	1.47	36.12	4,056.47	272.01
Consumers with Children	0.54	1.68	53.77	4.50
Consumers without Children	1.47	59.10	5,530.26	388.89

Note: This table summarizes the number of distinct cards, number of transactions, total restaurant sales, and total online food delivery service sales in each panel of the data, each of which is measured in millions. In particular, the data is separated by different types of consumers and different types of transactions.

Next, zip code-level characteristics are considered. The sample is aggregated at a monthly level by zip code, and contains 478,000 observations. There are roughly 30,000 zip codes observed in the data over the duration of the sample. Within these zip codes, approximately 1.5 million cards are used in approximately 61 million transactions. Descriptive statistics are presented in Table 2, including the monthly expenditure at restaurants and on online food delivery services, as well as monthly per-card spending at restaurants and on online food delivery services. Summary statistics of different panels are presented in the Appendix. The Appendix also provides visualizations of the differences in distributions of total restaurant spending and online food delivery spending between different panels of the data.

In order to have a valid study design, the entry of online food delivery services must be observable and heterogeneous over time and location. The entry of online food delivery services was validated on a city-by-city basis by examining the growth of the fraction of

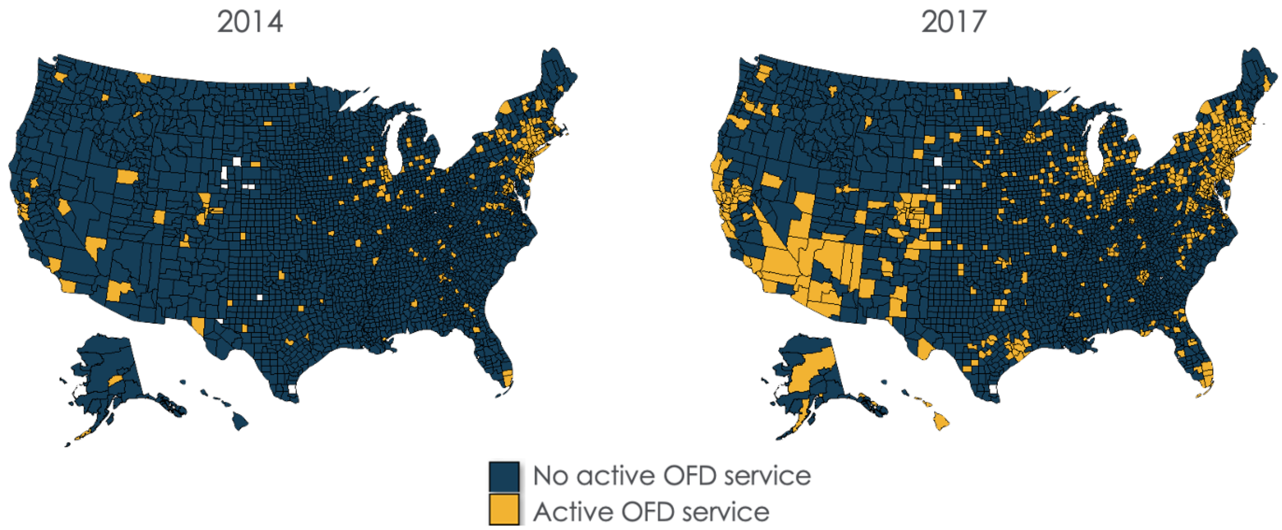
Table 2: Descriptive Statistics

	Mean	**Median**	**Std. Dev.**	**10%**	**25%**	**75%**	**90%**
Panel A: Zip code-level							
Amount ($)	8,716	1,057	37,937	76	253	4,675	16,215
OFD Amount ($)	627	22	4,517	0	0	196	920
Panel B: Card-level							
Amount ($ per card)	184	163	146	55	106	229	313
OFD Amount ($ per card)	26	22	37	0	0	43	72

Note: The descriptive statistics above are generated from cards that transact on online food delivery services at some point during their lifetimes. Amount refers to the monthly dollar amount spent at restaurants and OFD amount refers to the monthly dollar amount spent on online food delivery services. The corresponding per-card entries estimate expenditure on restaurants and online food delivery services on a per-card basis.

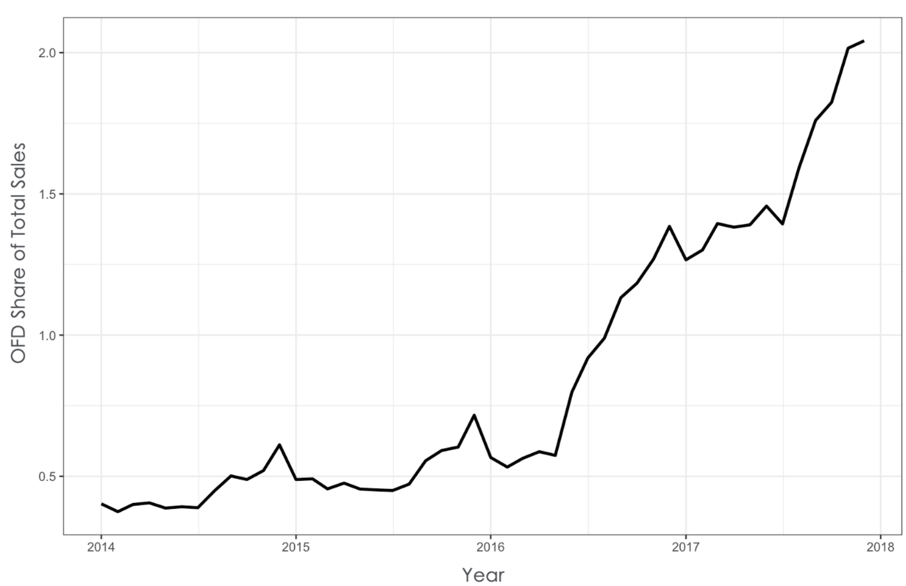
restaurant sales conducted on online food delivery services. Various newspaper articles and timelines found on the websites of online food delivery services were used to confirm that the entry is accurate. After confirming that online food delivery services are observable, it is important to understand where they are present and how they are expanding. It is expected that online food delivery services will first be present in larger metropolitan areas and grow outwards. Defining entry of online food delivery services as three consecutive months of greater than 0.3 percent of total restaurant sales being conducted on online food delivery services, county-level maps are generated for 2014 and 2017 in order to observe the expansion of these firms. Figure 1 compares the presence of online food delivery services in 2014 and 2017. These maps confirm that online food delivery services entered in counties with large cities and expanded outwards with their success over time. Trends in online food delivery services as a fraction of total restaurant spending are presented in Figure 2. This shows that there is very rapid growth in online food delivery services, even relative to total restaurant expenditure.

Figure 1: Trends in Online Food Delivery Sales



Note: These two maps show county-level entry of online food delivery services between 2014 and 2017. The gold counties are counties that have online food delivery services and the dark blue counties are those that do not yet have online food delivery services. An active county is defined as a county that has had greater than 0.3 percent of its restaurant sales conducted on online food delivery services in three consecutive months. It is important to note that the map does not change much with different thresholds on the percentage of restaurant sales conducted on online food delivery services.

Figure 2: Trends in Online Food Delivery Sales



Note: This figure shows the trend in the fraction of total restaurant sales spent on online food delivery services over time from 2014-2017. There is a clear upward trend that shows rapid expansion.

5 Empirical Approach

In order to quantify the effects of online food delivery services on restaurant sales, I propose a standard difference-in-differences model with a continuous treatment variable that exploits heterogeneity over time and across zip codes:

$$RestaurantSales_{zt} = \phi_z + \beta OFDSales_{zt} + \tau_t + \epsilon_{zt} \tag{1}$$

In this equation, *RestaurantSales* and *OFDSales* are measured in dollars-per-card at the monthly level. Note that ϕ_z and τ_t are fixed effects of zip code z and month t, which control for seasonality, trends, and variation across zip codes. The interpretation of this regression is relatively straightforward. The key coefficient, β, reveals the correlation between total restaurant sales and online food delivery service sales. Out of each dollar spent on online delivery services, β would be new sales caused by the entry of online food delivery services, whereas $1-\beta$ would become "crowded-out" from brick-and-mortar sales (i.e., $1-\beta$ dollars are displaced from brick-and-mortar sales for each dollar spent on online food delivery services).

A threat to the validity of the regression is caused by the non-random expansion of online food delivery services. Since online food delivery services choose to enter zip codes in which the expected demand is higher, results may have a downward bias. However, by sample construction, only cards that transact on online food delivery services are included, so the validity is only threatened by a correlation between demand and the timing of the market expansion. Based on anecdotal evidence of the industry settings and the nature of these firms, this assumption is supported. Further, card-level shocks to demand are not a concern because the data is aggregated at a zip code-level.

Examining the regression over different cuts of the data yields heterogeneity in the impact of online food delivery services. Time and weekday of transaction are available, so the data is separated into lunch, dinner, weekday, and weekend panels. Different seasons—cold and warm months—are also considered in order to determine the potential effect of seasons on online ordering behavior. Further, other card-level spending habits are available to differentiate consumers. The data is split into consumers that are characterized as those who have young children—determined by their spending at children's clothing and toy stores—and those that do not have children. Then, the impact in conservative states is compared to that in more liberal states, according to the 2016 presidential election results, as well as on a state-by-state basis. Finally, the impact of online food delivery services is quantified year-over-year in order to determine whether different levels of exposure to online food delivery services has caused incremental cannibalization of restaurant sales.

6 Results

This section includes the results of overall zip code analysis, as well as an examination of different cuts of the data. This includes time of purchase, type of consumer, and zip code-level characteristics with the goal of observing the types of consumers or purchasing behavior that may be driving the cannibalization of traditional restaurant sales. Further, I run the regression on a state-by-state basis and over different segments of time in order to determine whether there is incremental cannibalization of brick-and-mortar sales.

6.1 Main Results

The results of the baseline regressions are presented in Table 3. At the zip code-level, online food delivery services are generating incremental sales at restaurants that otherwise would not have occurred: the markets are expanding. However, they are not doing so perfectly because roughly half of each dollar spent on online food delivery services would have originally been transacted in-person at a restaurant. While online food delivery services might be important sales channels for some restaurants, they are partially cannibalizing offline sales. Further, breaking down the sample by the time of transaction yields different levels of substitution between these online and offline restaurant sales channels. While

Table 3: Baseline Regressions

	Dependent variable:						
	Total Restaurant Sales (per card)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Lunch	Dinner	Weekday	Weekend	Warm	Cold
OFD Sales	0.509***	0.419***	0.401***	0.471***	0.290***	0.512***	0.499***
(per card)	(0.016)	(0.016)	(0.014)	(0.016)	(0.010)	(0.026)	(0.016)
Observations	478,910	453,462	460,802	469,238	439,662	239,057	239,853
Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.352	0.311	0.286	0.319	0.206	0.371	0.439

*p<0.1; **p<0.05; ***p<0.01

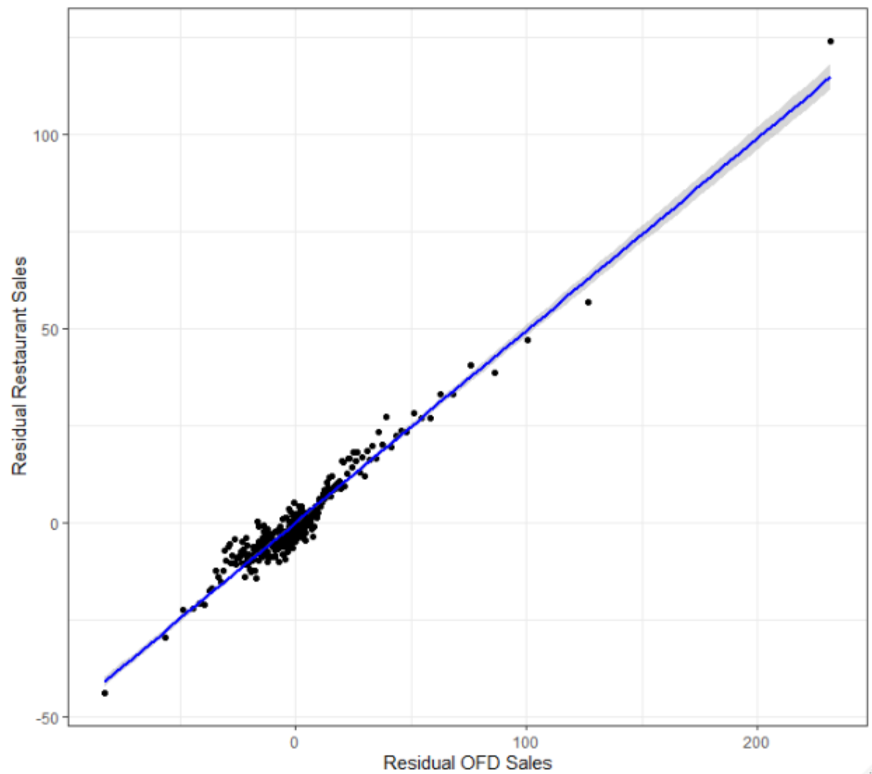
Note: Errors are clustered at the zip code-level. The columns refer to the type of transaction and type of consumer. For example, "lunch" refers to transactions that occurred prior to 5:00pm, "weekday" refers to transactions that happened during the work week, and "warm" refers to purchases that occurred during the summer months.

there is not a significant difference between lunch and dinner, or warm and cold weather transactions, Table 3 shows a great difference between weekday and weekend purchases.

The results are visualized in Figure 3, which maps residualized online food delivery service sales to residualized total restaurant sales in a non-parametrically binned scatter-plot. "Residualized" refers to de-meaning the data relative to between-date and between-zip code variation. There is a clear and robust linear relationship in the data, with the slope representing the percentage of each dollar spent on online food delivery service sales that is new to total restaurant sales.

The results of the analysis suggest that there are modest crowding-out effects caused by the introduction of online food delivery services. As shown above in Table 3, 30-50 cents of every dollar spent on online food delivery services is new, whereas the remainder is simply substituted away from brick-and-mortar sales. This suggests that, while causing some incremental sales, online food delivery services siphon away a fair portion from offline sales

Figure 3: Residualized Trends over Online Food Delivery Sales



Note: This is a non-parametrically binned residual-residual scatter-plot that shows trends in total restaurant sales over online food delivery service sales. The x-axis is the error term on the regression $OFDAmount_{zt} = \tau_t + \phi_z + \epsilon_{zt}$ and the y-axis is the error term on the regression $RestaurantAmount_{zt} = \tau_t + \phi_z + \epsilon_{zt}$. These regressions serve to not only de-seasonalize and de-trend the data over time, but also to de-mean it for between zip code variation. The resulting graph shows a highly linear trend in total restaurant sales as online food delivery service sales increase.

channels. The results are heterogeneous across different types of consumption, including lunch, dinner, weekend, and weekday transactions.

The heterogeneity suggests several possible mechanisms by which consumers are making the choice to substitute between in-person restaurant sales and online food delivery services. While the effects between lunch and dinner, as well as between summer and winter purchases, are similar with approximately 40-50 cents of every dollar spent on online food delivery services being new, there are striking differences between weekend and weekday purchases. Almost half of each dollar spent on online food delivery services during the work week is new, whereas only one third of each dollar spent on online food delivery services on the weekends is new. The remaining two thirds is substituted away from brick-and-mortar sales. Given time constraints during the week, the convenience of online food delivery services may be driving the higher level of substitution between online and offline channels.

6.2 Regional Differences

There also may be heterogeneity in the impact of online food delivery services across different regions of the United States. I break down different areas of interest, including the northern and southern states, as well as rural and urban areas. The results could identify the role of population density and the cost of travel on consumer choices.

According to Table 4, various broad regions—such as the northern and southern parts of the country—do not appear to exhibit different purchasing preferences when it comes to substitution between online and offline sales channels. However, rural and metropolitan centers exhibit much more heterogeneity. Almost the entirety of each dollar spent on online food delivery services appears to be new in rural areas, whereas urban parts of the nation substitute almost half of every dollar spent on online food delivery services from what would have been in-person restaurant purchases. The distance between a consumer's home and a restaurant is likely much smaller in urban areas than it is in rural areas.[9] The cost of travel

[9] This intuition is confirmed in a study conducted by the Centers for Disease Control and Prevention (Liu, Han, and Cohen 2015)

Table 4: Regional Regressions

	Dependent variable:			
	Total Restaurant Sales (per card)			
	(1)	(2)	(3)	(4)
	Urban	Rural	North	South
OFD Sales (per card)	0.466*** (0.018)	0.997*** (0.069)	0.509*** (0.020)	0.512*** (0.028)
Observations	400,647	42,041	334,866	144,044
Fixed Effects?	Yes	Yes	Yes	Yes
Adjusted R^2	0.363	0.304	0.357	0.339

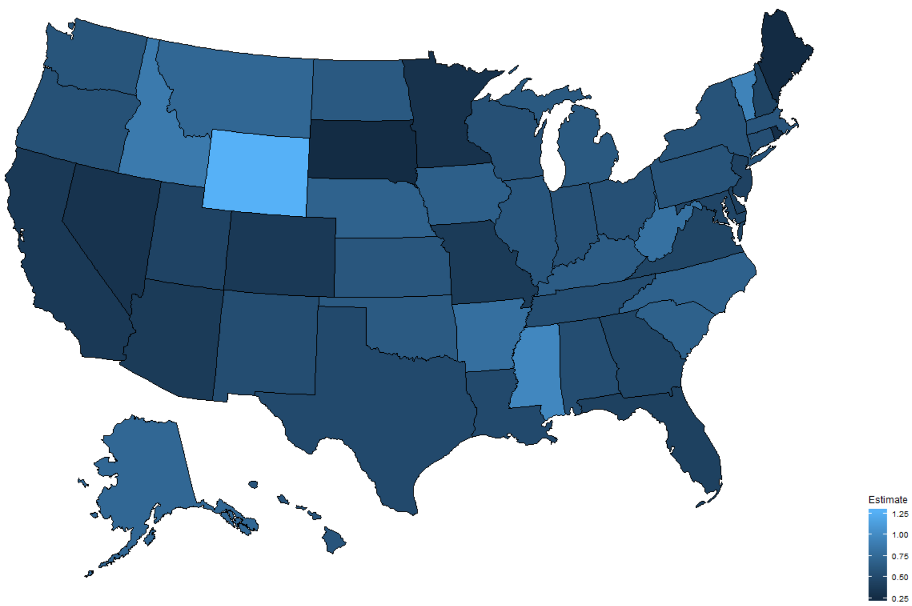
*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. The columns refer to different regions in the United States. The first two columns refer to zip codes that are designated as urban and rural, respectively; and the last two columns refer to zip codes that are in the northern and southern regressions of the United States, respectively.

could play an important role in the consumer choice model between online and offline sales channels when it comes to online food delivery services and restaurants.

Next, I include a state-by-state analysis of crowding-out effects by segmenting the data by state and running a regression on each subset. I find that the results differ greatly over each individual state. Although potentially under-powered due to fewer observations, Figure 4 reveals that more rural states, while noisier in the estimate of the coefficient, tend to see more additional restaurant sales with the introduction of online food delivery services, suggesting that higher availability of restaurants leads to more pronounced substitution effects. I present a table with state-level regression summaries in the Appendix.

Figure 4: State-by-State Coefficients



Note: This map shows state-level coefficients estimated by the regression $RestaurantSales_{zt} = \phi_i + \beta OFDSales_{zt} + \tau_t + \epsilon_{it}$, where *RestaurantSales* and *OFDSales* are measured in dollars per card and are aggregated to a zip code-month level. ϕ_i and τ_t are zip code and time fixed effects. Also note that the data is filtered such that each card must transact on online food delivery services at some point during its lifetime.

6.3 Consumer Heterogeneity

It is important to not only consider different types of purchases, but also different types of consumers. I examine heterogeneity in crowding-out effects caused by the entry of online food delivery services by breaking down consumers into several different categories, including those with and without young children, those who live in conservative versus liberal states, and quartiles of average monthly expenditure at restaurants. This analysis may provide insights into the mechanisms that drive substitution between online and offline sales channels at restaurants.

Table 5: Consumer Regressions

	Dependent variable:			
	Total Restaurant Sales (per card)			
	(1)	(2)	(3)	(4)
	Children	No Children	Conservative	Liberal
OFD Sales (per card)	0.530*** (0.026)	0.503*** (0.016)	0.544*** (0.020)	0.481*** (0.025)
Observations	233,043	477,536	247,769	230,031
Fixed Effects?	Yes	Yes	Yes	Yes
Adjusted R^2	0.150	0.347	0.327	0.372

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. The columns refer to consumers who (i) have children, (ii) do not have children, (iii) live in states that voted Republican in the 2016 presidential election, and (iv) those who live in states that voted Democrat in the 2016 presidential election.

Table 5 presents the results comparing different types of consumers. I find that the differences between consumers with children compared to those without is modest at just a few more cents of each dollar spent on online food delivery services being substituted away from brick-and-mortar sales. However, consumers living in conservative states appear to use online food delivery services for more new restaurant trips relative to those living in liberal states. Given that there is a high correlation between rural and conservative areas, as well as liberal and urban areas, this difference, while more modest than the differences between the strict distinction between urban and rural regions, is likely driven by the distance between restaurants and the consumer's home.

Table 6: Restaurant Spending Quartile Regressions

	Dependent variable:			
	Total Restaurant Sales (per card)			
	(1)	(2)	(3)	(4)
	Q1	Q2	Q3	Q4
OFD Sales	0.899***	0.592***	0.427***	0.457***
(per card)	(0.044)	(0.022)	(0.019)	(0.036)
Observations	75,669	128,894	142,060	132,287
Fixed Effects?	Yes	Yes	Yes	Yes
Adjusted R^2	0.120	0.091	0.097	0.274

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. The columns refer to zip codes that fall within the first, second, third, and fourth quartiles of average monthly expenditure at restaurants.

Table 6 shows that the differences between quartiles of average monthly expenditure are more pronounced. In the zip codes that fall in the bottom quartile of average monthly expenditure at restaurants, online food delivery services appear to bring new consumers to the table because nearly 90 cents of every dollar spent on online food delivery services is new, whereas just 10 cents is substituted away from brick-and-mortar sales. The results show that different spending behaviors may also be a significant factor in driving the choice between online and offline sales channels at restaurants because online food delivery services are drawing in those who don't typically spend at restaurants.

6.4 Incremental Cannibalization

While each of the regressions presented above describe potential mechanisms by which consumers are choosing to use online food delivery services over in-person restaurant meals, they tend to smooth the effect of online food delivery services over time. These services are a relatively new development, which have only gained their massive popularity in the past few years. Therefore, there are likely exposure effects that come along with the staggered entry of online food delivery services.

Table 7: Year-over-Year Regressions

	Dependent variable:		
	Total Restaurant Sales (per card)		
	(1)	(2)	(3)
	2014-2015	2015-2016	2016-2017
OFD Sales	0.574^{***}	0.434^{***}	0.462^{***}
(per card)	(0.033)	(0.017)	(0.016)
Observations	204,569	265,445	274,341
Fixed Effects?	Yes	Yes	Yes
Adjusted R^2	0.451	0.422	0.397

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. The years refer to the sample restrictions imposed on the analysis in these three regressions, which show incremental cannibalization with increased exposure to online food delivery services. Two year periods are included in order to smooth the effects, as the estimates were otherwise too noisy.

Table 7 presents regressions over pairs of years in the data in order to capture the exposure effects and incremental cannibalization; first, 2014-2015, then 2015-2016, and finally, 2016-2017. Pairs of years are chosen in order to smooth out the effect of sales cannibalization, as the estimates would otherwise become too noisy. The results show that the rate at which new sales are generated by online food delivery services is decreasing over time. This suggests that the incremental sales caused by the entry of online food delivery services decrease as there is more exposure to these new types of firms, meaning there is incremental cannibalization. Further, the results show that online food delivery services are “sticky:” once consumers start using them, they will likely continue using them, and even doing so on a more frequent basis.

Detailed regression tables over different cuts of the data, included in the Appendix, show that the incremental cannibalization is robust to the time of transaction, type of consumer, and various spending behaviors. There are several segments of the data that present particularly strong levels of substitution effects over time. First, during the warm months of the year, consumers begin to substitute more brick-and-mortar sales for online food delivery services. Given that summer is usually a time of relaxation, especially for younger customers, convenience may become more worthwhile.

Next, consumers without children feel the effects more strongly. Considering that this might be a younger crowd of cardholders, technical abilities may play a role in their increased levels of substitution. Now that online food delivery services have a foothold in the markets, those who know how to use their applications will be using them more frequently. Further, consumers in rich, northern, and liberal areas increase their cannibalization of brick-and-mortar restaurant sales over time. This suggests that consumers who have the resources to use online food delivery services and tend to frequent restaurants anyways will begin substituting more of their in-person restaurant visits for online food delivery services.

7 Conclusion

Online food delivery services have proliferated and rapidly changed the traditionally brick-and-mortar restaurant industry. This analysis contributes to a growing literature on substitution between online and offline channels by examining sales cannibalization in a new context. I used difference-in-differences methodology in order to determine the extent to which in-person restaurant sales are cannibalized by online food delivery services. Roughly half of each dollar spent on online food delivery services is new, whereas the remaining half is drawn away from brick-and-mortar sales.

Investigating crowding-out effects across different cuts of the data showed that there is much heterogeneity in the impact of online food delivery services. Weekend sales tend to be more cannibalized than those during the work week. Colder months of the year are also slightly more cannibalized than warmer months. Substitution between in-person restaurant sales and online food delivery services are far greater for consumers that tend to spend more at restaurants, whereas online food delivery services provide much higher incremental sales for those who do not frequent restaurants.

The heterogeneity across different types of consumers suggests that convenience is a major factor in determining whether a consumer will order a meal using online food delivery services. When there is a shortage of time, or if the weather is bad, a larger fraction of each dollar spent on online food delivery services is cannibalized from offline sales. Further, online food delivery services appear to be drawing in consumers that do not typically spend a lot at restaurants. Finally, examining sales on a year-over-year basis shows that the substitution of brick-and-mortar sales has increased over time. The change in effect is best seen during warm months in rich and liberal areas. This suggests that there is incremental cannibalization.

Popular media outlets often cite cases of individual restaurants' profitability getting slashed by high delivery fees from online food delivery services. Back-of-the-envelope calculations from the findings of this study show that although restaurant revenues are increasing by 1.2 percent, their profits are decreasing by 1.8 percent, confirming these suspicions.[10] Due to incremental cannibalization, revenue gained with online food delivery services will likely slow and cuts to profitability will accelerate over time.

[10]The calculation for increased revenue relies on the assumption that there is a 30 percent charge for each online food delivery order, 6 percent online food delivery services out of total restaurant sales, and half of each dollar spent on online food delivery services being new: $(0.7)(0.5)(6)$ - $(0.3)(0.5)(6) = 1.2$. The calculation for decreasing profitability relies on the assumption that profitability is constant across all restaurants and over time, as well as the other assumptions stated above: $(0.3)(6) = 1.8$. These figures must be interpreted with caution, however, as they group all types of restaurants together. Although unobservable, I hypothesize that online food delivery services benefit larger chains and harm smaller "mom-and-pop" restaurants.

Online food delivery services have shown no signs of slowing down in their rapid growth and expansion in the past decade. Understanding consumer behavior becomes of greater importance as these online channels gain momentum. The results of this study are particularly relevant in the age of COVID-19 as brick-and-mortar restaurant sales are greatly restricted by stay-at-home orders across the nation. Over time, the learned behavior of increased usage of online food delivery services in place of brick-and-mortar sales may result in the further acceleration of these changes.

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Appendix Table A1: Descriptive Statistics (Time)

	Mean	**Median**	**SD**	**10%**	**25%**	**75%**	**90%**
Panel A: Time of Transaction							
Lunch							
Restaurant Amount	126	109	113	36	69	156	219
OFD Amount	18	0	27	0	0	30	53
Dinner							
Restaurant Amount	96	85	74	32	57	117	159
OFD Amount	18	0	28	0	0	32	55
Panel B: Day of Transaction							
Weekday							
Restaurant Amount	144	127	115	44	82	177	243
OFD Amount	21	4	31	0	0	37	61
Weekend							
Restaurant Amount	73	64	65	24	43	89	122
OFD Amount	13	0	20	0	0	24	42
Panel C: Season							
Warm Months							
Restaurant Amount	187	166	145	56	107	232	317
OFD Amount	26	11	37	0	0	43	73
Cold Months							
Restaurant Amount	181	160	146	54	104	225	309
OFD Amount	26	11	37	0	0	43	72
Panel D: Year-over-Year							
2014-2015							
Restaurant Amount	174	153	143	50	98	217	302
OFD Amount	22	7	33	0	0	37	63
2015-2016							
Restaurant Amount	178	157	143	53	101	221	305
OFD Amount	21	0	34	0	0	35	63
2016-2017							
Restaurant Amount	191	170	147	59	112	236	321
OFD Amount	28	13	39	0	0	49	78

Note: The descriptive statistics above are generated from cards that transact on online food delivery services at some point during their lifetimes. Restaurant amount refers to the monthly dollar amount spent at restaurants per card and OFD amount refers to the dollar amount spent on online food delivery services per card.

Appendix Table A2: Descriptive Statistics (Consumer)

	Mean	**Median**	**SD**	**10%**	**25%**	**75%**	**90%**
Panel E: Type of Consumer							
Children							
Restaurant Amount	27	17	42	0	0	37	63
OFD Amount	5	0	14	0	0	0	19
No Children							
Restaurant Amount	184	163	145	56	106	228	312
OFD Amount	25	11	36	0	0	43	72
Panel F: Political Climate							
Conservative							
Restaurant Amount	174	151	148	47	94	217	303
OFD Amount	18	0	32	0	0	29	58
Liberal							
Restaurant Amount	195	175	142	68	120	240	322
OFD Amount	33	23	40	0	0	56	82
Panel G: Urban versus Rural							
Urban							
Restaurant Amount	186	167	135	63	113	229	309
OFD Amount	28	15	37	0	0	47	75
Rural							
Restaurant Amount	165	117	197	28	59	209	340
OFD Amount	7.5	0	24	0	0	0	24
Panel H: North versus South							
North							
Restaurant Amount	187	166	146	58	109	231	315
OFD Amount	28	15	38	0	0	49	77
South							
Restaurant Amount	178	156	145	49	97	223	308
OFD Amount	19	0	32	0	0	30	58

Note: The descriptive statistics above are generated from cards that transact on online food delivery services at some point during their lifetimes. Restaurant amount refers to the monthly dollar amount spent at restaurants per card and OFD amount refers to the dollar amount spent on online food delivery services per card.

Appendix Table A3: Descriptive Statistics (Spending)

	Mean	**Median**	**SD**	**10%**	**25%**	**75%**	**90%**
Panel I: Spending Behavior							
Quartile 1							
Restaurant Amount	93	71	101	19	38	116	184
OFD Amount	6	0	22	0	0	0	21
Quartile 2							
Restaurant Amount	142	127	105	57	92	167	228
OFD Amount	18	0	30	0	0	29	56
Quartile 3							
Restaurant Amount	184	171	104	100	138	209	265
OFD Amount	30	21	35	0	0	49	74
Quartile 4							
Restaurant Amount	277	245	183	145	197	312	418
OFD Amount	39	31	43	0	0	63	90

Note: The descriptive statistics above are generated from cards that transact on online food delivery services at some point during their lifetimes. Restaurant amount refers to the monthly dollar amount spent at restaurants per card and OFD amount refers to the monthly dollar amount spent on online food delivery services per card.

Appendix Table A4: Year-over-Year Panel Regressions (Time)

	Total Restaurant Sales (per card)	SE	Obs.	Fixed Effects?	Adj. R^2
Panel A: Time of Transaction					
Lunch					
2014-2015	0.460***	(0.027)	193,151	Yes	0.384
2015-2016	0.379***	(0.018)	250,543	Yes	0.347
2016-2017	0.384***	(0.017)	260,311	Yes	0.320
Dinner					
2014-2015	0.438***	(0.027)	196,382	Yes	0.343
2015-2016	0.352***	(0.018)	254,726	Yes	0.325
2016-2017	0.370***	(0.0363)	264,420	Yes	0.327
Panel B: Day of Transaction					
Weekday					
2014-2015	0.527***	(0.032)	200,231	Yes	0.415
2015-2016	0.405***	(0.016)	259,748	Yes	0.379
2016-2017	0.422***	(0.015)	269,007	Yes	0.359
Weekend					
2014-2015	0.314***	(0.015)	186,528	Yes	0.269
2015-2016	0.264***	(0.015)	242,391	Yes	0.244
2016-2017	0.284***	(0.013)	253,134	Yes	0.229
Panel C: Season					
Warm Months					
2014-2015	0.619***	(0.058)	101,547	Yes	0.470
2015-2016	0.510***	(0.025)	132,795	Yes	0.455
2016-2017	0.438***	(0.023)	137,510	Yes	0.430
Cold Months					
2014-2015	0.525***	(0.024)	103,022	Yes	0.451
2015-2016	0.433***	(0.019)	132,650	Yes	0.408
2016-2017	0.481***	(0.020)	136,831	Yes	0.395

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. Each panel represents different ways the data is grouped; the segments within each panel show the different levels of the grouping.

Appendix Table A5: Year-over-Year Panel Regressions (Consumer)

	Total Restaurant Sales (per card)	SE	Obs.	Fixed Effects?	Adj. R^2
Panel D: Type of Consumer					
Children					
2014-2015	0.538***	(0.018)	105,067	Yes	0.158
2015-2016	0.570***	(0.026)	124,169	Yes	0.161
2016-2017	0.527***	(0.037)	127,976	Yes	0.178
No Children					
2014-2015	0.575***	(0.033)	203,809	Yes	0.445
2015-2016	0.428***	(0.016)	264,596	Yes	0.416
2016-2017	0.452***	(0.015)	273,727	Yes	0.393
Panel E: Political Climate					
Liberal					
2014-2015	0.587***	(0.053)	98,629	Yes	0.459
2015-2016	0.396***	(0.024)	128,593	Yes	0.437
2016-2017	0.425***	(0.021)	131,402	Yes	0.420
Conservative					
2014-2015	0.557***	(0.029)	105,486	Yes	0.440
2015-2016	0.485***	(0.024)	136,246	Yes	0.406
2016-2017	0.505***	(0.024)	142,283	Yes	0.369
Panel F: Urban versus Rural					
Urban					
2014-2015	0.518***	(0.038)	171,363	Yes	0.458
2015-2016	0.393***	(0.018)	223,444	Yes	0.426
2016-2017	0.423***	(0.017)	229,311	Yes	0.406
Rural					
2014-2015	1.084***	(0.111)	17,684	Yes	0.454
2015-2016	0.900***	(0.079)	22,265	Yes	0.410
2016-2017	0.897***	(0.083)	24,357	Yes	0.351
Panel G: North versus South					
North					
2014-2015	0.590***	(0.042)	143,345	Yes	0.450
2015-2016	0.425***	(0.020)	186,255	Yes	0.429
2016-2017	0.454***	(0.018)	191,521	Yes	0.409
South					
2014-2015	0.527***	(0.039)	61,224	Yes	0.451
2015-2016	0.461***	(0.033)	79,190	Yes	0.405
2016-2017	0.487***	(0.032)	82,820	Yes	0.370

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. Each panel represents different ways the data is grouped; the segments within each panel show the different levels of the grouping.

Appendix Table A6: Year-over-Year Panel Regressions (Spending)

	Total Restaurant Sales (per card)	SE	Obs.	Fixed Effects?	Adj. R^2
Panel H: Spending Behavior					
Q1					
2014-2015	0.918***	(0.132)	32,144	Yes	0.217
2015-2016	0.780***	(0.089)	41,064	Yes	0.141
2016-2017	0.858***	(0.028)	43,525	Yes	0.189
Q2					
2014-2015	0.676***	(0.035)	55,345	Yes	0.192
2015-2016	0.588***	(0.031)	71,654	Yes	0.124
2016-2017	0.530***	(0.027)	73,549	Yes	0.169
Q3					
2014-2015	0.435***	(0.033)	60,610	Yes	0.193
2015-2016	0.395***	(0.027)	79,360	Yes	0.132
2016-2017	0.401***	(0.021)	81,450	Yes	0.159
Q4					
2014-2015	0.568***	(0.075)	56,470	Yes	0.390
2015-2016	0.350***	(0.030)	73,367	Yes	0.380
2016-2017	0.397***	(0.031)	75,817	Yes	0.338

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. Each panel represents different ways the data is grouped; the segments within each panel show the different levels of the grouping.

Appendix Table A7: State-by-State Regressions

State	Total Restaurant Spending (per card)	SE	Observations	Fixed Effects?	Adj. R^2
AK	0.738**	(0.295)	1,600	Yes	0.199
AL	0.532***	(0.080)	5,510	Yes	0.271
AR	0.799***	(0.199)	2,843	Yes	0.321
AZ	0.382***	(0.055)	9,173	Yes	0.314
CA	0.367***	(0.029)	48,432	Yes	0.414
CO	0.366***	(0.087)	9,815	Yes	0.488
CT	0.544***	(0.069)	8,264	Yes	0.334
DC	0.416**	(0.193)	2,749	Yes	0.295
DE	0.414***	(0.114)	1,806	Yes	0.296
FL	0.431***	(0.049)	26,419	Yes	0.298
GA	0.471***	(0.058)	11,392	Yes	0.426
HI	0.590***	(0.183)	1,823	Yes	0.242
IA	0.675***	(0.134)	5,078	Yes	0.383
ID	0.883***	(0.269)	2,099	Yes	0.293
IL	0.596***	(0.099)	19,265	Yes	0.395
IN	0.557***	(0.077)	9,173	Yes	0.431
KS	0.606***	(0.105)	5,111	Yes	0.324
KY	0.653***	(0.145)	5,352	Yes	0.274
LA	0.500***	(0.123)	4,802	Yes	0.323
MA	0.590***	(0.106)	15,076	Yes	0.303
MD	0.467***	(0.101)	10,571	Yes	0.353
ME	0.243	(0.420)	2,571	Yes	0.289
MI	0.626***	(0.051)	14,577	Yes	0.278
MN	0.304***	(0.074)	9,476	Yes	0.312
MO	0.378***	(0.058)	8,673	Yes	0.377

*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. This analysis is conducted on a state-by-state basis, where the leftmost column specifies that state for which the data was filtered. Note that some of the coefficients are outside of [0, 1]; this is expected given the noise caused by filtering down to such a small sample size.

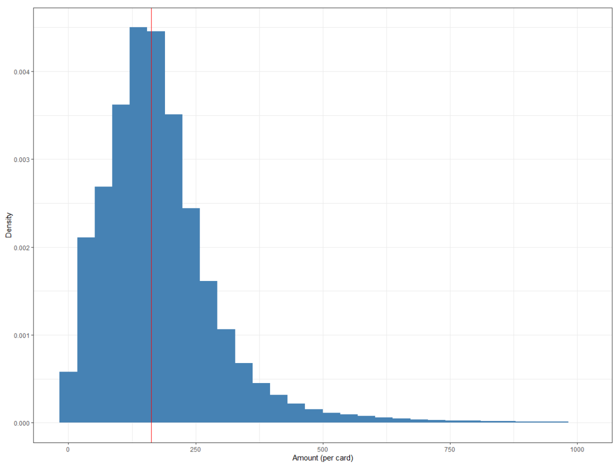
Appendix Table A8: State-by-State Regressions (continued)

State	Total Restaurant Spending (per card)	SE	Observations	Fixed Effects?	Adj. R^2
MS	0.979***	(0.195)	2,768	Yes	0.381
MT	0.740**	(0.289)	1,418	Yes	0.266
NC	0.690***	(0.196)	13,570	Yes	0.325
ND	0.628***	(0.192)	1,093	Yes	0.199
NE	0.701***	(0.125)	3,482	Yes	0.305
NH	0.455***	(0.123)	3,049	Yes	0.294
NJ	0.443***	(0.055)	20,062	Yes	0.306
NM	0.533***	(0.182)	2,566	Yes	0.285
NV	0.315***	(0.093)	4,094	Yes	0.386
NY	0.579***	(0.081)	35,511	Yes	0.411
OH	0.557***	(0.064)	15,896	Yes	0.293
OK	0.634***	(0.115)	6,195	Yes	0.396
OR	0.564***	(0.097)	6,069	Yes	0.313
PA	0.580***	(0.060)	25,373	Yes	0.353
RI	0.282**	(0.111)	2,240	Yes	0.246
SC	0.687***	(0.151)	5,817	Yes	0.267
SD	0.251	(0.186)	1,229	Yes	0.330
TN	0.531***	(0.089)	8,055	Yes	0.392
TX	0.502***	(0.041)	32,828	Yes	0.355
UT	0.453***	(0.101)	4,295	Yes	0.162
VA	0.462***	(0.076)	14,259	Yes	0.303
VT	0.949***	(0.318)	1,870	Yes	0.472
WA	0.592***	(0.083)	10,463	Yes	0.311
WI	0.559***	(0.064)	9,822	Yes	0.247
WV	0.812***	(0.159)	2,883	Yes	0.280
WY	1.28***	(0.217)	1,243	Yes	0.251

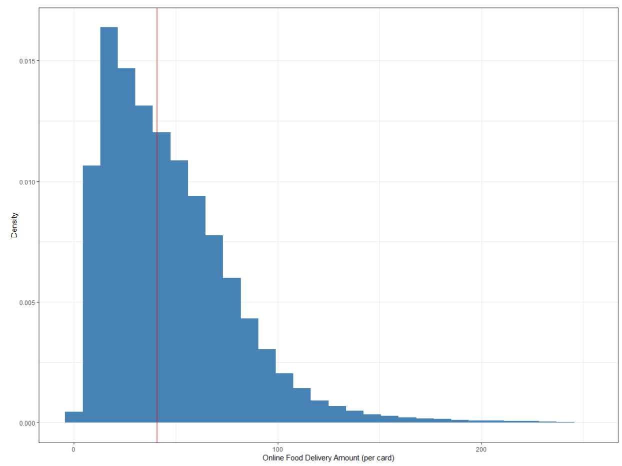
*p<0.1; **p<0.05; ***p<0.01

Note: Errors are clustered at the zip code-level. This analysis is conducted on a state-by-state basis, where the leftmost column specifies that state for which the data was filtered. Note that some of the coefficients are outside of [0, 1]; this is expected given the noise caused by filtering down to such a small sample size.

Appendix Figure A1: Density of Restaurant and OFD Expenditure (per card)
Overall



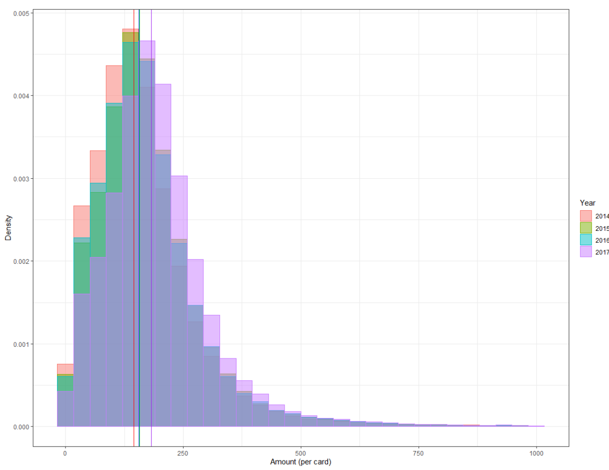
(a) Density of Amount (per card)



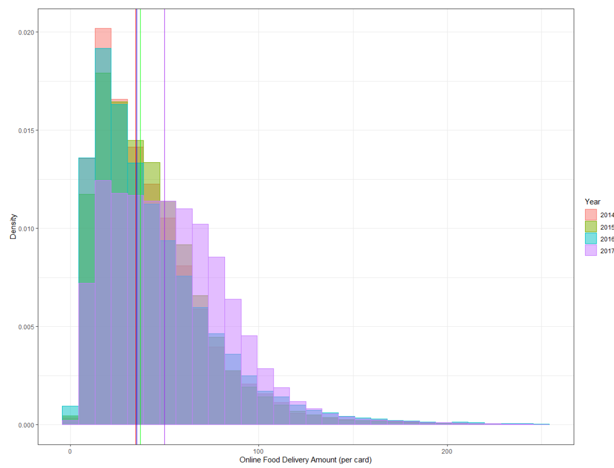
(b) Density of OFD Amount (per card)

Note: These histograms plot the relative frequency, or density of the amount spent at restaurants and the amount spent on online food delivery services on a per-card basis. These distributions will give a better idea of general consumer behavior in these different types of purchases. The density of the amount spent at restaurants appears to follow a normal distribution with a long right tail. The distribution of online food delivery service sales, which filters out transactions of zero dollars, is more centered to the left, but has a longer right tail.

Appendix Figure A2: Density of Restaurant and OFD Expenditure (per card)
Year-over-Year



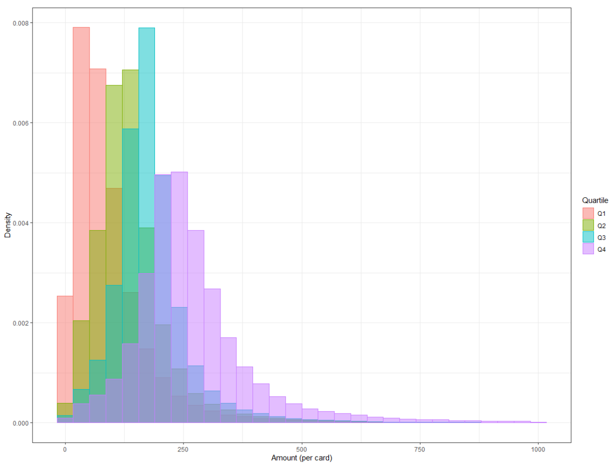
(a) Density of Amount (per card)



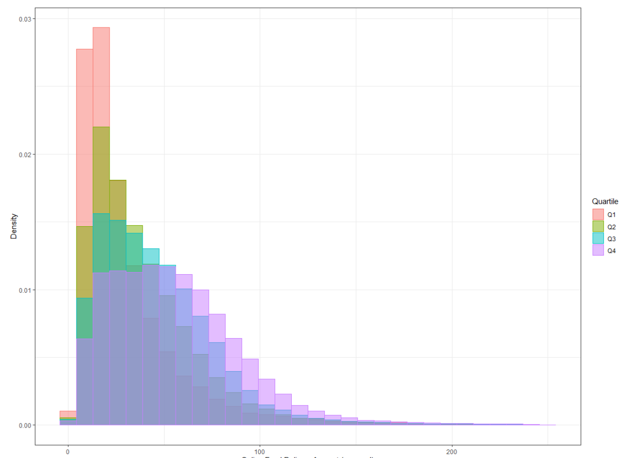
(b) Density of OFD Amount (per card)

Note: These histograms plot the relative frequency, or density of the amount spent at restaurants and the amount spent on online food delivery services on a per-card basis broken down by years (2014, 2015, 2016, and 2017). The plot on the left shows that there is a modest shift to the right in per-card restaurant expenditure over time. The plot on the right shows that online food delivery services receive more per-card spending as time progresses. The distribution of online food delivery services also flattens out; there is more variation between consumers now as there is greater exposure to these types of services.

Appendix Figure A3: Density of Restaurant and OFD Expenditure (per card)
Quartiles of Monthly Expenditure



(a) Density of Amount (per card)



(b) Density of OFD Amount (per card)

Note: These histograms plot the relative frequency, or density of the amount spent at restaurants and the amount spent on online food delivery services on a per-card basis broken down by quartiles of average monthly restaurant expenditure at the zip code-level. The plot on the left shows that, unsurprisingly, the distribution per-card restaurant expenditure of those in zip codes in the lowest quartile of restaurant spending is far to the left; as the quartiles of restaurant spending increase, the distributions shift to the right and widen. The plot on the right follows similar trends, although the differences in the distributions between quartiles do not change that much, just the wideness of the distributions.