A New Order? Digital Disruption and Entrepreneurial Opportunities

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ABSTRACT. Does the rise of digital marketplaces primarily benefit large incumbent firms or facilitate the entry of entrepreneurs, including those from minority backgrounds? This paper studies the growth of food delivery applications in the UK—UberEats and Deliveroo—and their impacts on local restaurants. To study this, I construct a novel dataset that measures the staggered spatial expansion of these apps and I employ a dynamic difference-in-differences framework. I find that app entry increases local restaurant counts (by 35%) and employment (by 12%) over four years and does not crowd out dine-in expenditures. This increase is driven by the entry of small and independent businesses, with ethnic minority entrepreneurs gaining disproportionately from lower entry costs and reduced dependence on prime locations. This democratization in entrepreneurship fosters greater diversity in cuisine offerings, enhancing consumer choice.

Key words: Technological Change, Gig Economy, Entrepreneur, Minority, Digital platforms
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1. INTRODUCTION

Digital marketplaces like Amazon, Alibaba, UberEats, and DoorDash have become significant sources of income for many entrepreneurs. Yet, it remains unclear how this transformation affects the entrepreneurial landscape and the future of work. Do these marketplaces democratize commerce by lowering barriers to entry and empowering small businesses? Do they expand access to entrepreneurship for marginalized groups? Or do they mainly benefit large, established firms that can better leverage economies of scale and algorithms? Understanding these questions is essential for assessing how digital technology will shape future opportunities and economic equality.

The answers to these questions remain unclear both theoretically and empirically. Theoretically, online marketplaces lower barriers to entry, encouraging entrepreneurship. If these lowered barriers are more equitable than traditional systems, underrepresented groups—who often face higher barriers—could benefit the most. However, they might also favor large firms due to reasons like enhanced search capabilities that help consumers find the best firms more easily, network effects that amplify the reach of established businesses, and algorithmic sorting that prioritizes popular firms. This could result in the rise of "superstar" firms and deter smaller entrepreneurs. Empirically, it is hard to study this question because digital platforms typically impact markets all at once, leaving few clear control groups, and in cases where comparisons might be possible, the necessary data is often unavailable.

In this paper, I assemble a novel dataset from multiple sources to examine this trend toward digital marketplaces through the lens of Food Delivery Applications (Food Apps) in the UK. Food delivery services like UberEats and Deliveroo are prime examples of digital marketplaces. They are a new fixture in the restaurant sector, which is a key contributor to both economic value and employment. Unlike many digital platforms that launch nationwide, food delivery applications expand in stages due to regional logistics, providing a quasi-experimental setting. I have compiled a novel dataset that tracks the staggered rollout of two major food delivery services in the UK, UberEats and Deliveroo, from 2013 to 2023, enabling me to analyze the impact using a dynamic difference-in-difference framework.

The two mentioned forces—lowering entry barriers and fostering "superstar effects"—are particularly relevant in this context. On the one hand, food apps may lower entry barriers. They allow businesses to operate with less physical space, eliminate the need for personal delivery fleets, and provide infrastructure for payments and marketing. I analyzed Reddit posts from restaurateurs using a large language model and found support for this. Many cite lower fixed costs as the main benefit of these platforms. Data also shows that app-partnered restaurants often have less expensive, smaller locations, and allocate less space to dining areas. These cost savings can especially benefit marginalized groups who might struggle more to cover the barriers in the traditional setting, promoting equality in entrepreneurship.

However, these apps may also create a "superstar" effect favoring larger or established restaurants. By broadening customer reach—a point emphasized in Reddit discussions—they intensify competition as more firms vie in an expanded market. The reduction of information asymmetry through ratings and reviews makes it easier for top-performing restaurants to stand out. This dynamic could lead to the rise of superstar firms, discouraging smaller entrepreneurs from starting a business.

To understand these competing forces, I developed a theoretical model that includes both lower entry costs and the superstar effect. The model clarifies the mechanisms at play and demonstrates their ambiguous net impact, prompting the need for empirical analysis to determine how Food Apps shape market structure and entrepreneurial opportunities. Accordingly, I conduct an empirical analysis leveraging the staggered spatial rollout of Food Apps in the UK. I trace their impact across three interconnected layers—firms, entrepreneurs, and the product market—and organize my empirical findings accordingly.

First, at the firm level, Food Apps significantly expand the overall size of the market, with the number of restaurants growing by 35% after four years of rollout. This growth leads to increased employment in the sector and is primarily driven by the entry of small and independent businesses. This is consistent with the notion that food apps lower barriers to entry, and small entrepreneurs, who often face challenges such as limited access to finance and lack of economies of scale, benefit the most from these platforms. Consumer data corroborates the market expansion, indicating that users choose food apps in addition to dining in rather than as a substitute. Nonetheless, there is also a higher rate of restaurant closures, aligning with the notion that intensified competition from market integration forces out less productive firms.

Second, at the entrepreneurial level, ethnic minority entrepreneurs gain more from these platforms. By inferring entrepreneurs' backgrounds based on their names sourced from Companies House, I find that all ethnic groups except White British entrepreneurs experience significant positive impacts from the expansion of food delivery apps.

Third, at the product market level, opening up food entrepreneurship to different ethnic groups results in greater diversity in the products offered, benefiting consumers. I show entrepreneurs often create dishes that reflect their backgrounds. As more diverse entrepreneurs enter the market, the variety of cuisines grows. This is evidenced by a significant increase in the number of cuisines available through these platforms and a decrease in the Herfindahl-Hirschman Index (HHI) based on cuisine types. This increased diversity counters concerns that platforms might lead to standardization or homogenization of culinary offerings. Instead, the platforms promote culinary diversity, enriching consumer choices.

I also explore mechanisms that are consistent with the disproportionate benefits for minority entrepreneurs. One hypothesis is that these groups are less productive and only enter the market when barriers are lowered. However, the data does not support this explanation: migrant-run app-partnered restaurants exhibit comparable productivity—measured by Google Maps ratings—to both migrant-run restaurants that are not on Food Apps and app-partnered restaurants that are not run by minorities.

A more plausible explanation is that these groups face greater traditional barriers to entry, such as limited capital, networks, and discrimination. Food delivery apps reduce and level these barriers, creating more equal opportunities. Supporting this, I find that food apps enable minority entrepreneurs, who are more likely to face capital constraints, to open businesses in more affordable areas—a pattern not observed among non-minority entrepreneurs. This aligns with descriptive evidence from Reddit, where restaurateurs cite the reduced need for prime locations as a key reason for joining these platforms. Moreover, inferring customers' backgrounds from Google Maps reviews, minority-run restaurants on platforms do not appear to attract a different racial clientele than offline establishments, suggesting that changes in customer demographics are not driving the benefits to minority entrepreneurs.

My empirical strategy, using the staggered rollout of two major food delivery applications, helps us control for multiple potential confounding factors. First, it accounts for location-specific differences that remain constant over time, such as the baseline rate of entrepreneurship or purchasing habits in different economic areas. Second, it adjusts for time-related effects that influence everyone equally, such as the rise in remote work increasing demand for food delivery. Third, it accounts for trends in outcome variables that differ across locations but follow a consistent pattern, like rich and urban locations exhibiting different trends than others. This last issue is managed through a specification that includes the interaction of local economy indicators with time-fixed effects.

Despite these controls, unobserved trends might have influenced where platforms chose to expand first. Anecdotal evidence and discussions with industry experts suggest that platforms decide where to roll out based on whether a region has enough customers to justify the overhead cost of entry. To test this, I conducted a machine learning exercise using over 30 spatial variables, including level indicators and trends, to predict rollout dates. The results show that variables like urbanization and income levels are key predictors. This suggests that rollout decisions are based on level variables, which are accounted for by location-fixed effects, rather than underlying trends.

To address this potential endogeneity issue more rigorously, I take three additional steps. First, I control for other local economic indicator variables interacting with time to account for the possibility that rich and poor regions might be on different trends. Second, I conduct an event study, which does not reveal any pre-existing trends, providing reassurance about the validity of the rollout assumption. Third, I use other industries as placebo controls, serving as proxies for local businesses, and find no significant impacts on them, further supporting the robustness of my findings. To also address recent econometric critiques of staggered difference-in-differences research designs, I confirm the robustness of the results by employing various alternative estimators.

This paper relates to several strands of literature. First, this paper engages with the literature on how digital technologies, often characterized as high fixed costs, benefit large firms and increase industry concentration (Hsieh and Rossi-Hansberg, 2023; Lashkari *et al.*, 2024; De Ridder, 2024; Aghion *et al.*, 2023). For example, De Ridder (2024) explain that technologies like IT reduce marginal costs but raise fixed costs. This shift leads to slower productivity growth and more market power for big firms. In contrast, I demonstrate a case where digital economy help small and independent businesses enter the market, particularly benefiting minority entrepreneurs. While the platform itself might be characterized as high fixed costs and low marginal costs, it enables operation within it with a low cost. This reveals that IT technology is not necessarily limited to benefiting top firms but can also level the playing field.

Second, the paper contributes to the literature on digital marketplaces' impact on entrepreneurship. Many studies focus on the effects of digital platforms on gig economy workers like drivers and couriers (Hall and Krueger, 2018; Koustas, 2018; Chen *et al.*, 2019; Cook *et al.*, 2021; Jackson, 2022). But few examine how these platforms impact entrepreneurs who sell goods and services directly, such as restaurant owners on food apps. Existing research often looks at niche platforms. For instance, Carballo *et al.* (2022) analyzes Peruvian firms and shows that a purely informational online platform reduces search costs in trade, benefiting smaller firms engaged in exporting. Other studies highlight how digital technologies can "level the playing field" for women entrepreneurs by mitigating challenges in face-to-face interactions (Poole and Volpe, 2023; Cong *et al.*, 2022; Sicat *et al.*, 2020; Pergelova *et al.*, 2019). My study advances this literature by examining a widely used platform, employing its staggered rollout as a research design, and showing how these applications reduce barriers for small businesses, particularly benefiting ethnic minority entrepreneurs.

Third, this paper builds on research about the economic impact of food delivery applications. I examine their effects on market structure, employment, and cuisine diversity. Previous studies, such as Raj and Eggers (2023); Raj *et al.* (2023); Raj and Choe (2023), show that platform penetration increases competition and exit rates among less efficient businesses while benefiting young and independent establishments by reducing search costs and enhancing digital capabilities.

Forth, this paper connects to the literature on talent misallocation and the resulting loss of potential. Hsieh *et al.* (2019) highlight how race- and gender-based barriers result in talent misallocation across occupations. Similarly, Bell *et al.* (2019) and Aghion *et al.* (2017) show that children from disadvantaged backgrounds face higher obstacles to becoming innovators, leading to "lost Einsteins." Akcigit *et al.* (2017) provide further evidence, showing that this correlation between parental income and inventor success holds historically. My paper expands this literature by addressing how these barriers extend to less high-status sectors, like the restaurant industry, and how digital technology can mitigate them. Reducing barriers in such industries is still very important, as entrepreneurship and firm ownership have been shown to be key in reducing the racial wealth gap (Lipton, 2022; Fairlie and Robb, 2007).

Finally, I contribute to the literature on how digital platforms influence the spatial distribution of economic activities. Fan *et al.* (2018) find that e-commerce reduces the fixed cost of market entry and the impact of distance on trade, and boosts production in smaller cities, while (Couture *et al.*, 2021) report limited economic benefits in rural areas. In urban contexts, most studies focused on Airbnb (Almagro and Domínguez-Iino, 2024; Calder-Wang, 2021; Garcia-López *et al.*, 2020; Schaefer and Tran, 2020). Specifically, Almagro and Domínguez-Iino (2024) finds that Airbnb expansion leads to an increase in tourism-focused amenities (e.g., restaurants) at the expense of local amenities. Looking at Uber, Gorback (2020) shows that ridesharing services enhance amenities and housing prices in areas with driving accessibility but poor transit options. Building on this literature, my study reveals how food apps, by reducing the necessity for prime locations, enable restaurants to relocate to more affordable areas within neighborhoods, thus redistributing economic activity spatially and potentially mitigating location-based barriers for small businesses.

The subsequent sections of this paper are structured as follows. The following section details the study context and data sources. In Section 3, I introduce a model to guide the analysis and provide evidence supporting the assumptions about how food apps influence entrepreneurship. Section 4 outlines the research design, focusing on the staggered rollout of food delivery applications and the methodological approach. The empirical findings in Section 5 show that technology boosts market entry, especially for small businesses. Ethnic minorities, who traditionally faced entry barriers, benefit disproportionately. Finally, I demonstrate how the rise in entrepreneurship among ethnic minorities spills over into the product market, leading to greater product diversity. Section 6 concludes.

2. Context and Datasets

Food delivery applications have grown fast worldwide. In 2024, global revenue is expected to hit $1.2 trillion (Statista, 2024), with the UK market projected at $50 billion.

These applications broadly provide two types of services to businesses. In the first model, consumers order through the app, and the platform coordinates and handles the delivery on behalf of the restaurant. In the second model, consumers order through the app, but the establishment handles the delivery, with the platform just facilitating matching and information exchange. This paper focuses on the first model, examining Uber Eats and Deliveroo, the two biggest platforms based on this business model, which launched in the UK in 2013 and 2016, respectively.[1]

I now introduce the datasets used in my analysis, highlighting their role in the empirical exercise, and providing descriptive evidence where applicable.

2.1. Consumers.

I use two datasets to track consumer use of food delivery apps.

Fable Spending Data. I use the Fable dataset to track consumer spending on food delivery apps. It covers 3820,000 monthly users and includes over a billion bank transactions from January 2016 onward. The data captures the first part of each consumer's postcode and full merchant postcodes, allowing me to see spending on Deliveroo and UberEats across different regions and over time. Table A1 columns (1) and (3) compare Fable users to the UK population. The dataset shows a slight bias toward younger and wealthier individuals.

Using Fable, Figure 1 shows the market share of Food Apps in the restaurant sector over time, focusing on UberEats and Deliveroo. Usage has steadily increased, with two major peaks during the UK's nation-wide COVID-19 lockdowns. Although the pandemic accelerated Food App adoption, the trend has since stabilized without a notable decline.

National trends give an overall view but hide key regional heterogeneity. Figure 2 shows how food delivery application use varied across local authority districts in 2022. In some areas, more than 30% of restaurant spending went through UberEats and Deliveroo, while other areas saw little use. The box-and-whisker plot in Figure A1 complements this by showing the distribution of FDP usage over time, highlighting persistent and possibly widening geographic disparities.

[1] Just Eat is another major player in the UK market, but it is not considered in this study for two reasons. First, Just Eat predominantly operates under the second business model, particularly in its early stages, which is not the focus of this analysis. Second, because Just Eat relies on restaurants to manage their own deliveries, its expansion across the UK was more rapid and lacked the staggered rollout seen with Deliveroo and Uber Eats (Keeble *et al.*, 2021), making it less suitable for the empirical strategy employed here.

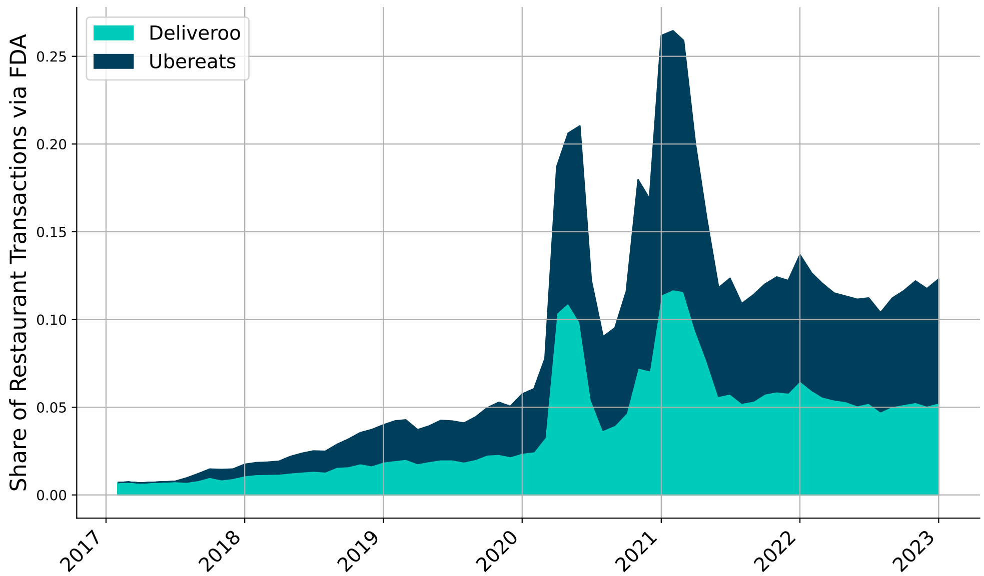
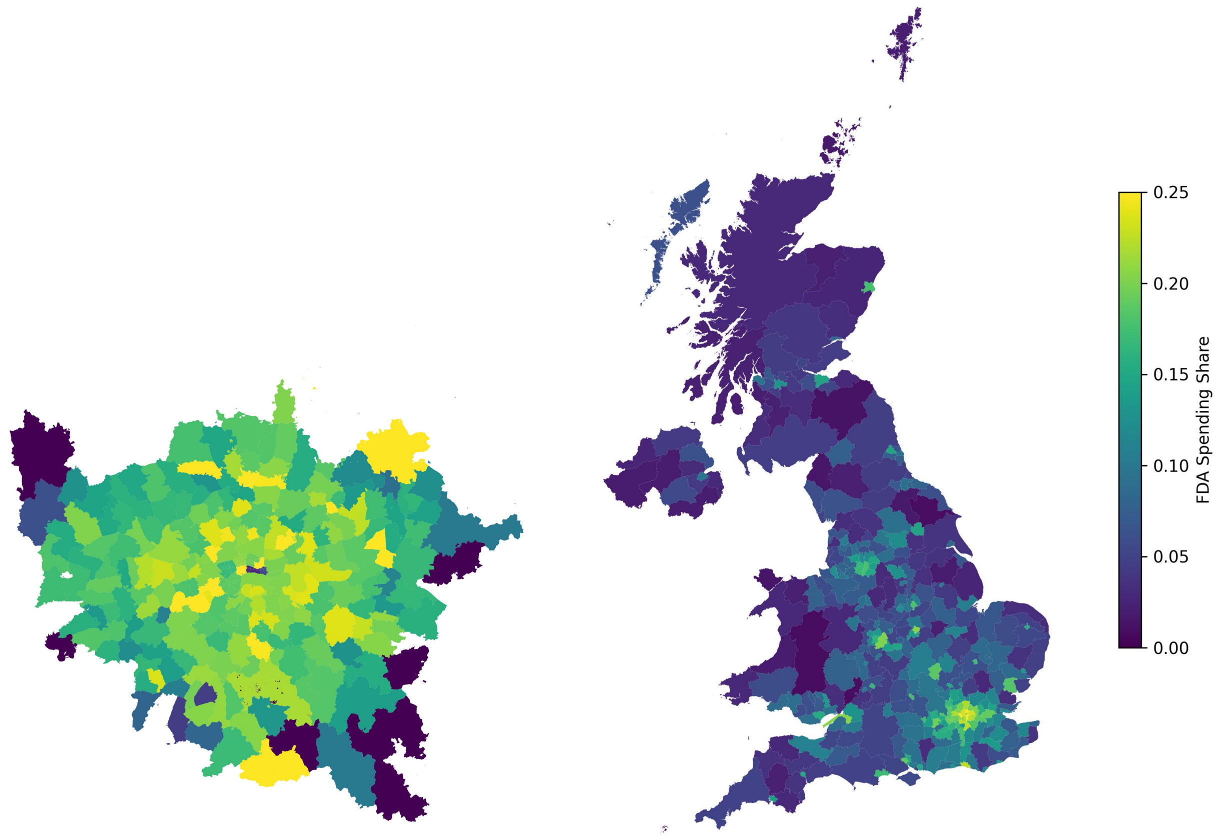


Figure 1. *Notes:* This figure illustrates the trend in the share of transaction values made through various food delivery applications (Food Apps) from 2017 to 2023. Data is sourced from Fable is limited to transactions in GBP and for MCC codes pertaining to eating establishments. The stacked areas represent the proportion of transaction values corresponding to Deliveroo and Uber Eats.

Kantar's Worldpanel. I use Kantar's Worldpanel data, both the Take-Home Purchase Panel and the Out-of-Home Purchase Panel, for this analysis. Though smaller in sample size, Kantar's Worldpanel offers richer details compared to Fable, allowing me to examine substitution behavior, such as whether increased Food App usage leads to a decrease in other restaurant spending methods. Kantar's Worldpanel tracks household purchases through its fast-moving consumer goods (FMCG) panel, which covers about 30,000 British households. The Take-Home data focuses on food and drinks bought intended for "take-home" consumption, including items from supermarkets, convenience stores, and smaller vendors. The panel records both in-store and online purchases by scanning barcodes, and capturing product details like price, size, and nutrition.

The Out-of-Home (OOH) panel is a smaller subset of 7,500 individuals. It tracks food for consumption outside the home. This includes "on-the-go" food —which may have been purchased from the same sources as at-home food—as well as all meals from restaurants and takeaways, even those eaten at home. Participants record their purchases using a mobile phone app. Although multiple members from one household can participate, over 85% of households are represented by just one individual. To ensure consistency, I aggregate purchases from multiple household members into a single household-level record as in O'Connell *et al.* (2022).

Table A1 provides summary statistics for demographics and spending variables in the Kantar Worldpanel dataset, comparing them with the Fable dataset and official statistics from the ONS. The income levels in the Kantar data show closer alignment with ONS figures compared to those



(a) Greater London

(b) UK

Figure 2. *Notes:* The figure represents a geographical visualization of the Food Delivery Application penetration (Deliveroo and UberEats) across postal districts in greater London (panel a) and various local authority districts in the UK (panel b) for the year 2022. The data, derived from Fable, includes transactions associated with the restaurant industry. Each district's Food App penetration is calculated as the proportion of outgoing spending tagged with references to food delivery services Uber Eats and Deliveroo relative to total outgoing spending in the restaurant industry within the spatial unit. This map was created by correcting mislabeled or outdated district names using a bespoke mapping function, ensuring alignment with the most current administrative boundaries as defined in the 2022 local authority district dataset.

from Fable. For age distribution, Kantar's dataset is intermediate between Fable and ONS data. Females make up 60% of the Kantar sample.

Fable shows a higher spending on food delivery applications compared to Kantar's Worldpanel. Several factors explain this difference. First, since Kantar's data is based on self-reporting, there may be variations in how participants record their purchases (for example, a food app order might be classified under general delivery). Second, Fable's sample is slightly younger, over-representing those more likely to use delivery services. Additionally, the share of food delivery app spending within total restaurant spending is lower in Kantar's data because it encompasses a broader range of purchases, such as snacks and non-restaurant items, which dilutes the proportion attributed to delivery platforms. Lastly, Fable captures only bank card transactions, potentially increasing the reported share of delivery platforms by excluding cash transactions more common in non-Food App purchases.

2.2. Restaurants.

I collected data on restaurants from various sources, including scraped listings, official records, and market research companies.

Full records of all restaurants on Deliveroo, and UberEats. I created a dataset by scraping restaurant listings from Deliveroo and UberEats. This dataset covers the period from Q1 2021 to Q1 2024, with quarterly updates. For each restaurant, I recorded the name, type of cuisine, and location[2]. An example of the scraped data for each platform is presented in Figure A3. This data allows me to track platform expansion into different regions, as will be detailed later.

While it is possible that some registered outlets were not captured in our searches, the number of identified outlets in the last batch, 2024 Q1, aligns with reported figures of approximately 63,000 for UberEats in 2023 and 50,000 for Deliveroo in 2024 (John Lewis Partnership, 2023; Deliveroo, 2024), bolstering confidence in the dataset's completeness.

Restaurants on Google Maps. I compiled a dataset of over 180,000 restaurant listings from Google Maps, likely covering most, if not all, restaurants in the UK, including those on delivery platforms and those that are not. The dataset includes key details such as cuisine type, average ratings, price indicators, and reviewer information. I construct the data by leveraging both the official Google Maps API and web scraping techniques, with details on the extraction process provided in Section A2. Figure A4 panel (a) showcases a sample restaurant listing on Google Maps along with the extracted data points.

One key advantage of this dataset is the inclusion of reviews. I extracted over 6 million reviews from all listed restaurants in the UK. This data serves two purposes: first, to infer the ethnicity of each reviewer based on their name and profile picture, allowing for an analysis of the racial profile of customers; second, to estimate each restaurant's launch date by identifying its earliest review, assuming reviews begin soon after the restaurant opens. Figure A4 panel (b) showcases a sample of restaurant reviews on Google Maps along with the extracted reviewers' names.

I matched about 60% of app-partnered restaurants with their corresponding entries on Google Maps using names, coordinates, and the Google Places API service, as detailed in Section A4. Table A2 compares app-partnered restaurants with non-partnered ones, showing that app-partnered restaurants tend to have higher prices, more reviews, lower average ratings, and are generally newer.

Local Data Company (LDC). LDC is a commercial research consultancy specializing in retail locations throughout Britain. LDC's data includes detailed information such as business types, exact locations, names, opening and closing dates, and cuisine type. They collect this data by physically surveying premises every 6 or 12 months. In addition, LDC continuously updates its

[2]If a restaurant stays on the platform, it will appear in multiple waves of our data. However, tracking it across these waves is challenging due to naming variations and incomplete names in earlier datasets.

information by monitoring news sources to capture any interim changes, keeping the database current between surveys.

With data on both cuisine types and exact locations, LDC allows for cuisine type analysis at different spatial levels. Since the dataset includes restaurant names, we can match establishments directly with other sources at the restaurant level using these names, as explained in Section A4. Its focus on physical inspections, rather than just registration records, also helps capture the real operations of businesses, including cases where a single registered entity operates under multiple brands.

UK Business Structure Database (BSD). This database is an annual extract of the Inter-Departmental Business Register (IDBR). It includes almost all UK businesses registered for VAT or with at least one employee under the PAYE system. The dataset contains key details such as the first half of the postcode, employment numbers, turnover, industry classification (SIC), legal status (e.g., sole proprietor, partnership), foreign ownership, company start date, and termination date.

Due to the anonymized nature of the data, I cannot directly match individual restaurants with other sources. Instead, for local authority-level analysis, I rely on aggregated data at the unit level (individual sites or enterprises).

I utilize the BSD to validate and cross-reference findings from other sources like LDC. Since the BSD is an official registry of legal businesses, while the LDC collects data through market research, comparing the two allows me to uncover the extent of practices like "virtual" brands where one registered kitchen operates multiple brands. Furthermore, the BSD's comprehensive coverage of non-restaurant industries facilitates placebo and falsification tests.

Company House. The Company House dataset provides information on business directors, including names, ages, and nationalities. While it does not directly include ethnicity, I infer these attributes using name-based analysis, a common method in economic research. The basic premise is that names can provide clues about race, reflecting cultural traditions or established naming conventions. Typically, this method involves training a model on a large dataset of names annotated with race or ethnicity labels. Once trained, the model can infer race or ethnicity for names in an untagged dataset. I detail the procedures for this inference in Appendix A3.

A limitation of the Company House dataset is that it covers only incorporated firms at the enterprise level. However, as demonstrated in Table A3, which shows both local units (establishments) and enterprises (firms) from IDBR, this limitation does not significantly constrain the analysis. Incorporated firms constitute 79,000 of the 101,000 total enterprises (approximately 78%) and 95,200 of the 118,000 local units (about 81%). This indicates that the dataset captures the majority of businesses, with unincorporated firms representing a smaller portion. The second limitation—having data only at the enterprise level—is also less consequential, as the difference between enterprises and local units among incorporated firms is less than 16%, and even smaller when focusing on smaller restaurants. Additionally, since non-incorporated businesses are probably more likely to be immigrant-owned firms, the findings on ethnic minority entrepreneurs may actually underestimate the true effects.

2.3. Other Datasets.

The Business Register and Employment Survey (BRES). To look at employment, I use BRES. BRES is a vital source of official employment statistics, providing detailed information on the number of employees and employment across different industries and regions in the UK. [3]

Price Paid Data. This dataset is a comprehensive dataset published by HM Land Registry, detailing property transactions in England and Wales since 1995. It includes key information such as the transaction date, price paid, property type, and full address details including postal code, local authority, district, and county. I use this data to construct an index to assess whether the Food App allows restaurants to relocate to more affordable areas.

To construct the index, I calculate the median property price for all transactions in each postcode over the past 10 years, adjusting for inflation. The median number of transactions for each postcode was six transactions. For postcodes with no transactions, which are rare, I impute the missing price data using nearby postcodes with known values. I use haversine distance to identify the 10 closest postcodes and take the median of their transaction prices to fill in the missing values.

Valuation Office Agency (VOA) Data. I use data from the Valuation Office Agency to obtain detailed information on commercial properties at the postcode level. The VOA, an executive agency of HM Revenue and Customs, assesses properties for council tax and business rates in England and Wales. The dataset includes estimated property valuations, the number and types of rooms, and the floor space of each room. While the Price Paid Data provides actual transaction prices at the postcode level, offering direct insights into property costs, the VOA data offers government-estimated valuations of commercial properties. I match this information to restaurants using their postcodes. Since most postcodes contain only one restaurant, matching is straightforward. For postcodes with multiple restaurants, I average the property characteristics. This helps me analyze how property features relate to restaurant operations and their participation in food delivery applications.

Reddit Data. I also use data from Reddit, an online platform where users discuss topics in communities called subreddits. I collect posts from two subreddits: *r/Restaurateur* and *r/RestaurantOwners*. These communities consist of restaurant owners and industry professionals sharing experiences and advice. I identify posts that indicate an intention to use food delivery apps. Analyzing these posts using a large language model, as will be discussed shortly, helps me understand the motivations and concerns of restaurant owners regarding the adoption of these platforms.

3. Conceptual Framework

In this section, I provide an intuitive framework that captures the two mechanisms through which food delivery applications might impact restaurants and entrepreneurship. The formal model and detailed derivations are presented in the Appendix A5.

[3] When using this dataset, I use data from 2015 onwards. This is necessary because the figures from 2015 to 2022 include businesses registered for PAYE but not for VAT, which makes them inconsistent with pre-2015 data.

I build upon the firm heterogeneity model in monopolistic competition introduced by Melitz (2003). Consumers have preferences represented by a standard Constant Elasticity of Substitution (CES) utility function with elasticity $\sigma > 1$ over a continuum of differentiated products denoted by the set Ω of available varieties. This specification leads to a demand function for each variety as follows:

$$q(\omega) = YP(\omega)^{-\sigma}P^{\sigma-1}$$

Where P is the aggregate price index, defined as:

$$P = \left(\int_{\Omega} P(\omega)^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}$$

On the production side, firms face uncertainty regarding their productivity levels. To enter the market, a firm must pay an entry cost. Upon entry, each firm draws its productivity φ from a Pareto distribution with shape parameter θ. After observing their productivity, firms decide whether to produce or exit the market. Operating firms incur a fixed production cost f_d and have constant marginal costs inversely proportional to their productivity. Labor is the only input in production.

There are two key equilibrium conditions in this framework. First, the Zero Cut-off Profit condition determines the productivity threshold φ^* below which firms cannot profitably operate in the market. Firms with productivity $\varphi < \varphi^*$ choose to exit. Second, the Free Entry condition ensures that the expected profits from entering the market equal the entry cost. It determines the market equilibrium price index.

I explore two mechanisms through which food delivery applications might affect this equilibrium:

3.1. **Reduction of Fixed Costs.** Food delivery applications can reduce the fixed production cost f_d by providing essential services such as logistics, payment systems, marketing, and customer service infrastructure. Also, restaurants no longer need to invest heavily in physical space, delivery fleets, or administrative overhead, lowering the barriers to operation and allowing more firms—especially smaller and less capitalized ones—to enter the market.

Empirical evidence supports this assumption. Analyzing restaurateurs' experiences shared on Reddit, detailed in the Appendix A6, I found that restaurant owners frequently cite cost reductions as a key motivation for adopting food delivery applications. Using a large language model to classify the content of these posts, I observed that key reasons include reductions in marketing expenses, leveraging platform-provided infrastructure, lowering on-premise delivery costs, and decreasing premises costs.

These insights align with additional data on the physical characteristics of restaurants partnering with food delivery applications. As shown in Figure A6, these restaurants are located in cheaper areas, are smaller in size, and allocate less space to dining compared to non-partnered establishments. This pattern persists even after accounting for postal districts, suggesting even within a postal distinct food app restaurants tend to sort into cheaper and smaller areas. By relying on app-driven visibility and logistical support, these restaurants can avoid the fixed costs associated with large, high-exposure locations.

3.2. **Superstar Effects.** There are several reasons to believe that food delivery platforms might lead to a superstar effect and a winner-takes-all dynamic in the restaurant industry. First, these platforms expand consumer reach, allowing restaurants to serve customers beyond their immediate locality while they reduce information asymmetries through features like ratings, and reviews. This will help the top firms to be known and thus help the top player benefit the most. Similarly, algorithmic sorting can disproportionately benefit top-performing restaurants. Third, network effects can amplify the success of popular establishments, as increased orders and reviews further enhance their visibility on the platform.

In my model, I capture this potential for a superstar effect by assuming a decrease in the shape parameter θ of the Pareto distribution of firm productivities, making the distribution more fat-tailed. A lower θ implies greater heterogeneity among firms and increases the likelihood that highly productive firms will dominate the market. While I do not model the specific mechanisms leading to this decrease in θ, this approach allows the model to represent various underlying reasons that might contribute to a winner-takes-all outcome.

Empirical evidence further substantiates this modeling assumption. Analysis of posts from Reddit shows that "Expanding Customer Reach" is the most cited reason for adopting food delivery applications. This expansion allows firms with higher productivity or better offerings to access a larger market, amplifying their competitive advantages. As these firms attract more customers from a broader area, they can capture a significant share of the market, potentially at the expense of less productive competitors.

3.3. **Propositions.** Based on the developed framework, I derive the following propositions. Detailed mathematical derivations and proofs for each proposition are provided in Appendix A5.

Proposition I. *If a new technology disproportionally benefits superstar firms, i.e., leading to a more fat-tailed distribution of firm productivities—meaning it decreases the shape parameter θ of the Pareto distribution—it will decrease the equilibrium number of firms in the market.*

This proposition reflects the superstar effect, where increased market integration, algorithmic sorting and etc favor highly productive firms, leading to market concentration and a reduction in the total number of operating firms.

Proposition II. *If a technological improvement reduces the fixed cost of production f_d, it will increase the equilibrium number of firms in the market.*

By lowering f_d, food delivery platforms make it feasible for more firms to operate profitably. Next, I consider what happens when a technology does both: lowers fixed costs and benefits superstar firms.

Proposition III. *If a new technology both disproportionately benefits superstar firms (decreasing the shape parameterθ) and reduces the fixed production cost f_d, then the equilibrium number of firms in the market will increase if and only if the proportional decrease in the fixed cost is sufficiently large relative to the decrease in θ. Specifically, the increase in the number of firms will occur when:*

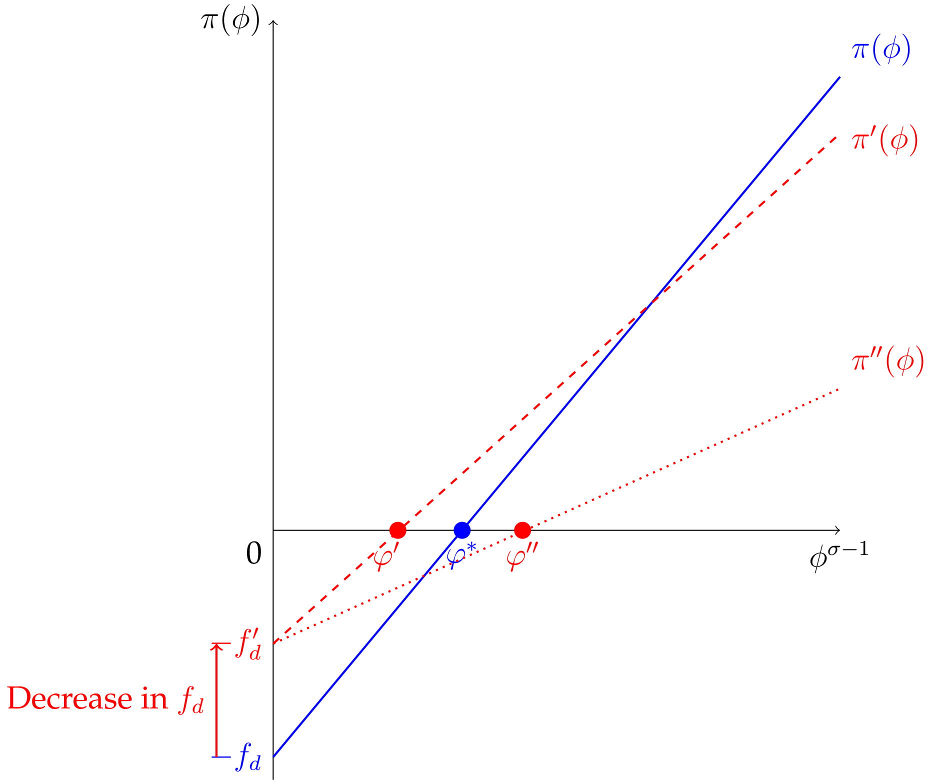


Figure 3. *Notes:* This figure shows a schematic representation of the effect of a technological change that simultaneously reduces fixed costs (f_d) and alters the productivity distribution to reflect superstar effects on the profit as a function of productivity. The reduction in fixed costs is represented by an upward shift in the y-intercept, while the change in slope captures the impact of superstar effects as well as the reduction in the fixed cost. Depending on the magnitude of these two opposing forces, the productivity cutoff (φ^*), below which firms exit the market, may shift to the right (φ') or to the left (φ'').

$$\frac{\Delta f_d}{f_d} > \left(\frac{\sigma - 1}{1 + \theta - \sigma}\right) \frac{\Delta\theta}{\theta}$$

where Δf_d and $\Delta\theta$ represent the absolute decreases in f_d and θ, respectively.

Thus, the net effect on the number of firms is ambiguous. It depends on which force is stronger: the reduction in fixed costs or the superstar effect. If the fixed cost reduction is larger, more firms enter, promoting entrepreneurship and diversity. If the superstar effect dominates, the market becomes more concentrated, and fewer firms operate.

Also, we can see that higher σ amplifies the impact of the superstar effect, as consumers become more sensitive to price and quality differences among products. This heightened sensitivity leads consumers to substitute more readily towards highly productive "superstar" firms, allowing these firms to capture a larger market share and further dominate the market.

Figure 3 illustrates how such a technology impacts the productivity cutoff φ^* in the model. When fixed costs decrease due to the introduction of food delivery platforms, the profit function shifts upward (reflecting lower entry barriers), but the slope also decreases due to the reduction in the price index (see Appendix A5). In one scenario (dotted line), the slope becomes sufficiently flatter, and the cutoff shifts right to φ^*, allowing more firms to enter as reduced fixed costs make the operation profitable for less productive firms. In another scenario (dashed line), the cutoff shifts left to φ^*, indicating that the dominance of "superstar" firms prevents less productive firms from entering despite the lower fixed costs.

The theory demonstrates that the net impact on the number of restaurants and the entry of new entrepreneurs depends on the relative strength of these opposing forces. Because the outcome is ambiguous, we need empirical investigation to understand how food delivery platforms affect the restaurant industry. This is the focus of the next section.

4. Research Design and Rollout of Platforms

To examine the impact of food delivery applications on the restaurant industry, I utilize an event study design based on the staggered rollout of Deliveroo and UberEats across regions. This staggered rollout provides a quasi-experimental setting, allowing us to isolate the causal effects of these platforms by leveraging variations in their rollout dates. The baseline specification I will estimate is:

$$y_{st} = \alpha + \Sigma_j \beta_j \mathbb{1}[t = E_s + j] + \mu_s + \lambda_t + X_s \times \lambda_t + \epsilon_{st} \tag{1}$$

In this equation T represents the year, S is the spatial unit (either a Postal District or a Local Authority, as discussed further later), and E_s is the year when spatial unit S gained access to the food delivery apps. This approach compares the pre- and post differences in outcomes between regions (or individuals residing in regions) where a food delivery application was introduced and those in regions where the food delivery application has not yet been introduced or will not be introduced. The specification includes both region and year fixed effects, as well as controls for region population and GDP (X_s) interacted with time. Assuming that, in the absence of the platform rollout, outcomes would have followed similar trends, and that the treatment effects are uniform across locations and time, the coefficient β represents the average treatment effect on the treated (ATT) due to the introduction of Food Apps.

With these assumptions, the two-way fixed effects (TWFE) model allows us to address several potential concerns that could otherwise impede causal interpretation. Firstly, it rules out the possibility that time-invariant fixed differences in individual spending behavior or regional restaurant market features are driving the results. For instance, one might suspect that richer, more urban areas and their residents have different baseline outcomes. By incorporating location fixed effects, I can mitigate these concerns.

Secondly, the results are unlikely to be influenced by the outcomes that evolve uniformly across individuals or restaurants in different locations. For instance, global trends such as the increased reliance on takeaway foods due to the rise of remote working arrangements may affect all individuals and restaurants across different locations in a similar manner. Time-fixed effects help account for this.

However, the rollout of platforms might still be correlated with trends in the outcome variable. This is relevant because the rollout decisions were strategic rather than random. For example, denser urban areas gained access to both major food delivery applications earlier, suggesting that the expansion decision is not random. Nonetheless, the absence of pre-trends, which I will discuss, makes it unlikely that platforms timed their rollout to coincide with sudden shifts in local demand. Instead, the evidence indicates that level variables, rather than trends, influenced where the platforms decided to expand.

Specifically, several factors that do not concern trends in outcome variables guided the rollout sequence. First, establishing an office or operational infrastructure incurs fixed costs, so platforms prioritized markets that were sufficiently dense to justify these initial investments—leading them to focus on larger urban areas first. Second, scale constraints due to limited platform capacity, especially in the early stages, influenced the sequence of expansion. Third, to capitalize on network effects, platforms aimed to simultaneously attract a critical mass of users and restaurants, which was more feasible in tech-savvy areas with a higher concentration of restaurants.

A simple machine learning-based feature selection process supports this claim that level variables, rather than underlying trends, are deriving the rollout dates. In this exercise, as detailed in section A7, I employ the best selector method and consider a list of variables comprising both fixed location characteristics and level and trends of economic indicators as potential predictors. The analysis indicates that variables such as population, GDP, and urbanization are the best predictors of rollout dates rather than trends.

I take extra measures to ensure the validity of the parallel trends assumption. First, I apply the estimator from Borusyak *et al.* (2024) to detect any pre-existing trends. In the robustness checks, I (1) re-estimate the main analysis using alternative methods from De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021); (2) include local economic indicators to account for different trends based on the economic situations of regions; (3) add rollout-group-specific linear time trends; (4) test placebo industries and find no significant results; and (5) repeat the analysis excluding the COVID-19 period and excluding London.

4.1. **Defining Market.** Defining geographic markets in the context of food delivery applications is complex due to the fluid nature of delivery boundaries. This complexity arises primarily for two reasons. First, regardless of how spatial units are defined, a restaurant located near the borders of one unit may serve customers in neighboring units, complicating the assignment of restaurants and consumers to specific markets. Second, platforms dynamically adjust delivery zones based on factors such as demand, traffic, and courier availability.

To address this issue, I use two geographic units for analysis: local authorities and postal districts. Local authorities are administrative regions in the UK, with around 400 in total. A postal district, on the other hand, is defined by the first half of a postcode (e.g., "NW1" for "NW1 0QA"), known as the outward code. I employed Geographic Information Systems (GIS) and the National Statistics Postcode Lookup to map restaurant geolocations and postcodes to their respective postal districts. Although sizes vary, 2011 census data shows the median population of a postal district was 22,574, with an average of 24,714 (Office for National Statistics, 2015).

Each spatial unit offers distinct advantages for analysis. The local authority level provides a broader market definition, which helps mitigate concerns about spillover effects. Additionally, some outcome variables are only available at the local authority level, or using postal districts might give rise to issues related to small sizes in each cell. Moreover, policies and economic decisions are often made at this broader administrative level, making findings particularly relevant for local policymakers.

However, the local authority level approach comes with drawbacks, such as reducing spatial variation and potentially masking important differences within the area. Local authorities can be quite diverse in their economic structure, demographics, and geographic size, which can obscure local heterogeneity. On the other hand, postal districts offer more spatial variation and better align with how food delivery applications define their delivery areas, making them a useful unit of analysis. Given these strengths and weaknesses, where data permits, analyses will be conducted at both the local authority and postal district levels to fully leverage the benefits of each approach.

4.2. **Pinpointing the Rollout Date.** I use the earliest rollout of Deliveroo or Uber Eats as a benchmark for food delivery application presence. Capturing this rollout is challenging due to platforms' non-standard rollout strategies. In some cities, a platform might launch services comprehensively, while in others, it might adopt a gradual, neighborhood-by-neighborhood approach. This variation can even exist within the same city, with different platforms adopting distinct rollout strategies. For example, Deliveroo might launch city-wide, while UberEats might opt for a phased neighborhood approach. This inconsistency makes it difficult to determine the appropriate spatial unit for recording rollout—whether at the city, borough, or postal district level. Additionally, platforms often do not usually announce expansions through press releases or media coverage.

To overcome these challenges and precisely pinpoint platform rollout dates into each spatial unit, I adopt a data-driven approach, utilizing distinct methodologies tailored to each platform's unique characteristics and rollout patterns.

4.2.1. *Deliveroo:* Deliveroo does not, at least systematically, disclose its rollout dates. To determine the rollout dates of this platform across different regions, I utilized two primary sources.

First, I systematically extracted location data for all restaurants listed on UberEats from the first quarter of 2021 through the second quarter of 2024 on a quarterly basis. This approach provided snapshot pictures of all restaurants on the platform at different points in time. Aggregating this information for all restaurants within a spatial unit, I estimate each platform's rollout date into that region based on the earliest restaurant among all restaurants. Table A4 shows the details of these scraped restaurants.

Second, for regions where Deliveroo began operations before 2021, I used a commercial dataset that arguably recorded the entire universe of restaurants on Deliveroo since its inception in the UK. This dataset, compiled through scraping exercises by data providers, starts from 2013 to 2021.

The few instances where media coverage has provided rollout dates for Deliveroo (Daily Mail, 2019) align with the timing of restaurant appearances in this dataset, validating its accuracy.

4.2.2. *UberEats:* First, like for Deliveroo, I systematically extracted location data for all restaurants listed on UberEats from the first quarter of 2021 through the second quarter of 2024 on a quarterly basis. The presence of a restaurant in a particular postal district or local authority is used as an indicator of UberEats' operation in that region, even though the coverage may not be exhaustive. Table A4 summarizes these scraped restaurants.

To identify regions penetrated by UberEats prior to 2021, unlike Deliveroo, where I had access to an external dataset tracking restaurants on the platform, no comparable resource exists for UberEats. Instead, I relied on three additional sources and selected the earliest rollout date from these.

- I reviewed Uber's official announcements, which listed rollout dates for several regions on the Uber Newsroom website until August 2017. This provided 23 rollout dates, as listed in Table A5. Since city or region names do not always align with postal districts, I assign a postal district to the announced region if the majority of its spatial area falls within the mentioned city or region.
- UberEats maintains a coverage page listing regions it serves in the UK.[4] By leveraging the Internet Archive, I tracked historical versions of this page, identifying regions listed at various points in time. I retrieved coverage information for the following dates: 8 May 2020, 24 May 2020, 3 June 2020, and 30 September 2020. Figure A7 shows this.
- For each of the regions listed in the coverage page of ubereats at 2021Q1, I used indexed pages in Google to find the indexed dates for that specific region. That is, I utilised Google search queries to determine the indexing dates of these city pages by searching for the presence of the city-specific URLs within Google's indexed pages. While Google reindexes periodically, the index date provides a point in time at which we can be certain that a link for that particular region existed, thus offering a conservative estimate for the earliest possible rollout date.

Finally, among these sources—systematic restaurant data extraction, official announcements, historical coverage analysis, and Google indexed dates—I selected the earliest indicated rollout date for each region as the rollout date of UberEats. This approach ensures that the earliest possible evidence of UberEats' operation in a region is used to determine the rollout timeline.

Using the identified rollout dates for each platform, panels (a) and (b) of Figure 4 show Deliveroo's and UberEatsr rollout across postal districts, highlighting considerable spatial variation. Appendix Figure A8 presents similar patterns at the local authority level. As expected, there is slightly less variation at this broader level, since the presence of a single restaurant in an area qualifies it as treated, leading to earlier treatment assignment across all units. Using alternative definitions, such as the second or third restaurant, yields similar results since many restaurants join around the same time. The comparison between panel (a) and panel (b) shows that Deliveroo, as expected, was the first to penetrate most areas. Appendix Figure A9 further explores this by

[4]https://www.ubereats.com/gb/location

directly comparing the rollout dynamics of both platforms, highlighting areas served exclusively by one or neither platform.

The steady expansion of food delivery applications has significantly increased their geographic and population reach over time. Figure A10 illustrates the coverage of postal districts and local authorities by UberEats or Deliveroo over time. Panel (a) shows a steady increase in postal district coverage starting from 2014, with a notable rise around 2016–2018, reaching about 78% by 2024. Panel (b) indicates a faster increase at the local authority level, nearing 100% coverage by 2022. This earlier coverage at the local authority level reflects its broader geographic scope, as discussed. To account for population differences across regions, Figure A11 combines platform rollout dates with postal district population data, illustrating that by 2023, nearly 90% of the population had access to at least one app-partnered restaurant.

4.2.3. *Addressing Concerns of Market Boundaries and Accessibility.* A key concern in this context is the potential misclassification of areas as treated based on the presence of a single restaurant partnering with a food app. This may not reflect the broader accessibility of the platform for other entrepreneurs in the same area. For instance, other restaurants might lack the ability to join due to their specific location within the area, limitations in the platform's capacity, or if the initial partnership was an isolated experiment. Such factors might limit the ability of other businesses to join the platform, affecting the general applicability of the treatment effect.

However, this issue, if present, likely understates the actual impact of treatment, as the measure does not fully capture the full scope of accessibility. This means any significant effects we find are conservative estimates. That said, to address this concern, I implemented three approaches to demonstrate that, on average, entrepreneurs in treated areas had access to partner with the platforms:

First, focusing on Deliveroo—for which I have detailed restaurant-level data before and after 2021—I analyzed the pattern of restaurant sign-ups following the platform's rollout. As shown in Figure A12, there is a significant spike in the number of restaurants joining Deliveroo during the initial rollout phase, followed by steady growth over time. This pattern indicates that the platform was onboarding multiple restaurants simultaneously, not just a single establishment. Therefore, it is unlikely that capacity constraints or isolated experiments prevented other entrepreneurs from partnering with the platform in treated areas.

Second, I redefined the rollout timing within postal districts by identifying the earliest time any restaurant within a five-mile radius of the district's centroid joined Deliveroo. The centroid was calculated using the weighted average of restaurant coordinates, with weights assigned based on the number of Google Maps reviews, giving more influence to highly-reviewed restaurants. The results remained consistent.[5]

Third, I assessed restaurant accessibility on both platforms across all UK postcodes, comparing postcodes in treated regions with those in control. Figure A13 confirms that treated postcodes have significantly higher accessibility, particularly at greater distances. When defined at the local

[5]This analysis could not be conducted for UberEats, as regions treated before 2021 were identified at the region level rather than based on the presence of specific restaurants at the postal district level.

authority level in panel (b), results remain similar, though the number of accessible restaurants decreases slightly in treated areas, which is expected due to the broader spatial classification. To further explore if the average number of accessible restaurants might mask variations in access across postcodes, I examined the extensive margin of access, specifically the share of postcodes with access to at least one Food App restaurant. Figure A14 shows that over 70% of postcodes in treated areas have platform access within 2km, compared to less than 10% in control regions.

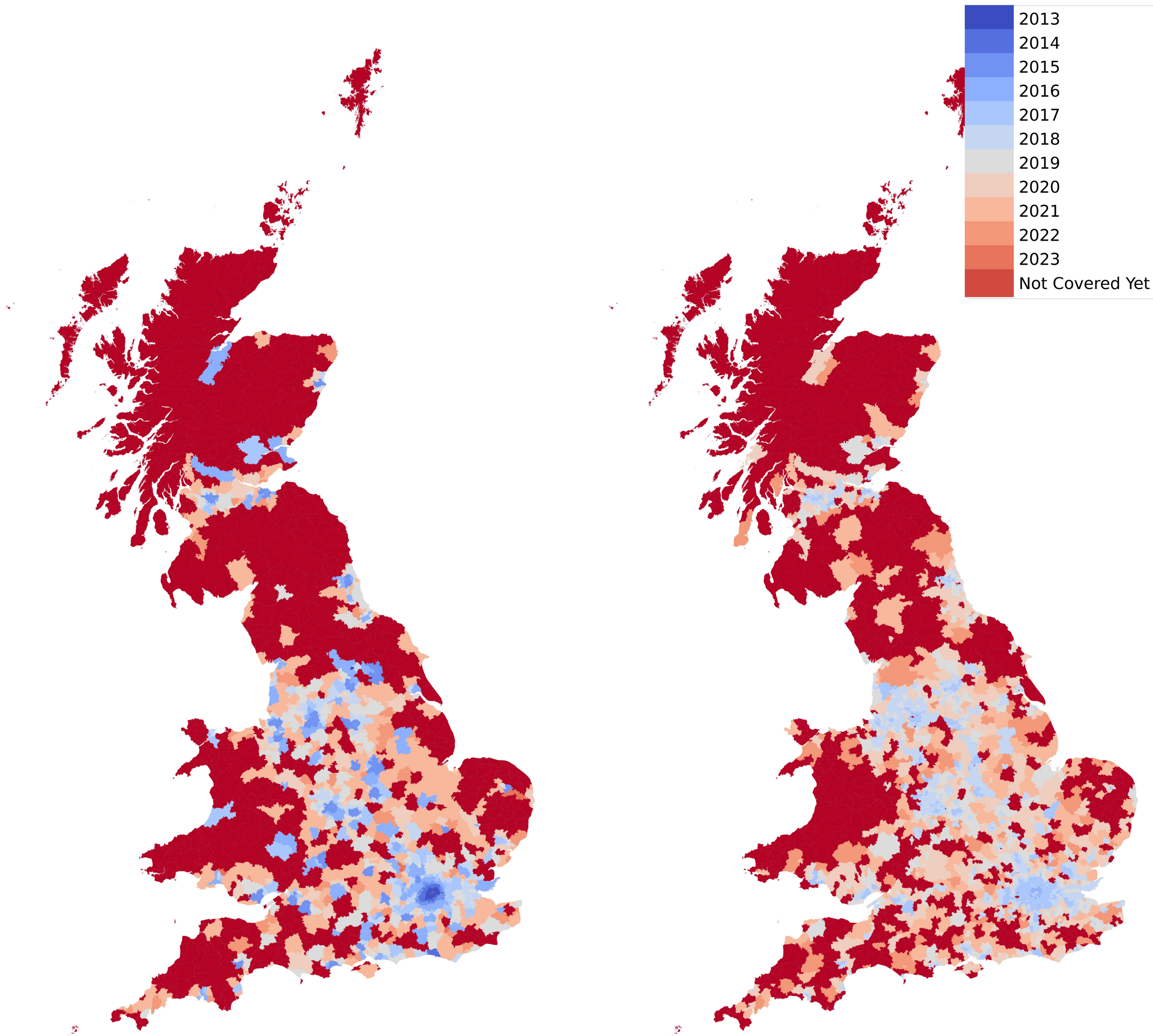
4.3. **Validation of Rollout Date.** To assess whether the platform rollout measure captures not only access but also actual consumer usage, I conduct an event study regressing food delivery spending—measured using data from Fable and Kantar Worldpanel— on the staggered rollout measure, as specified in equation 1. The results, shown in Figures A15 and A16, indicate that spending on food delivery applications increases following their rollout in both datasets. This consistency provides robust evidence that the platform rollout measure accurately reflects consumer access and usage.

The graph shows near-zero pre-trend coefficients, ruling out two possibilities: mismeasurement of platform rollout, where consumers had access earlier than recorded, and meaningful use of platforms from non-residential locations, such as workplaces. This suggests that most orders are likely placed from home, or that both residential and workplace addresses gain access to food delivery applications around the same time.

In this chapter, I outlined the methodology for defining the market and pinpointing the rollout dates of the platforms. I showed that individuals in regions identified as having access to the platforms indeed have access to multiple restaurants. Furthermore, I used two spending datasets and showed my identified rollout dates align with the increase in spending on these platforms. In the following sections, I leverage this staggered rollout of platforms as a source of variation to explore the causal impacts of these e-marketplaces into three areas: first, on firms; second, on entrepreneurs; and third, on the product market.

5. Quasi-Experimental Effects of Platforms

This section explores the empirical evidence on how food delivery applications have transformed the restaurant industry. I structure the results into three parts: firms, entrepreneurs, and the product market. First, I analyze the firm-level effects, focusing on changes in the number of restaurants, including both new openings and closures, and examine how these trends differ across various types of establishments. Next, I turn to the entrepreneurs, examining the demographic and background characteristics of those who have benefited most from these platforms. If the costs associated with accessing digital platforms are more evenly distributed across demographic groups than traditional costs, these platforms could play a crucial role in making entrepreneurship more equitable. Then, I investigate the extent to which these impacts trickle down to the product market, influencing the variety of cuisines available to consumers. Finally, I explore underlying mechanisms and investigate the barriers in traditional brick-and-mortar settings that are potentially mitigated in an e-marketplace environment.

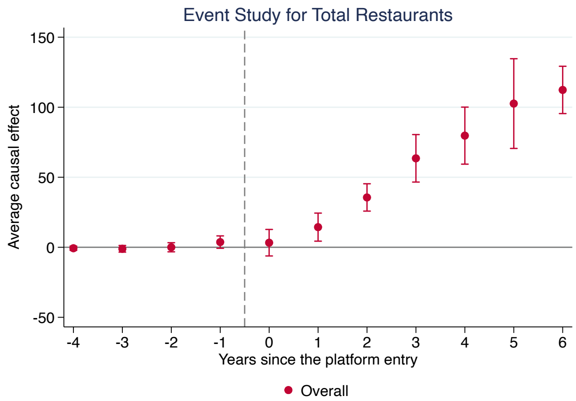


(a) Deliveroo Rollout

(b) UberEats Rollout

Figure 4. *Notes:* This map displays UK postal districts that have a minimum of one restaurant featured on Google Maps. Panel (a) depicts the introduction of the Deliveroo application, and panel (b) indicates the introduction of the UberEats application. The UK postal districts boundary file is sourced from here. A small number of postal districts could not be directly mapped due to updates in postal district definitions. These unmatched districts were associated with the closest matching district from the boundary file.

5.1. **Impact on Firms: Restaurant Market Dynamics and Industry Expansion.** I start by showing the impact on the number of restaurants. Figure 5 panel (a) shows a clear increase in the number of restaurants following platform rollouts in local authorities. On average, five years after the introduction of the platform, the number of restaurants rises by 100 units, which represents a 35% growth for the average local authority. These estimates are based on data from the Local



(a) Overall

(b) Independent vs Multiple

Figure 5. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on the total number of restaurants over time. Panel (b) shows the average causal effect on the number of independent versus multiple establishment restaurants. The x-axis represents the years since the platform rollout, and the y-axis shows the average causal effect. Data is sourced from the Local Data Company (LDC).

Data Company (LDC) and control for local authority and year fixed effects, as well as interactions between local GDP and population by year.

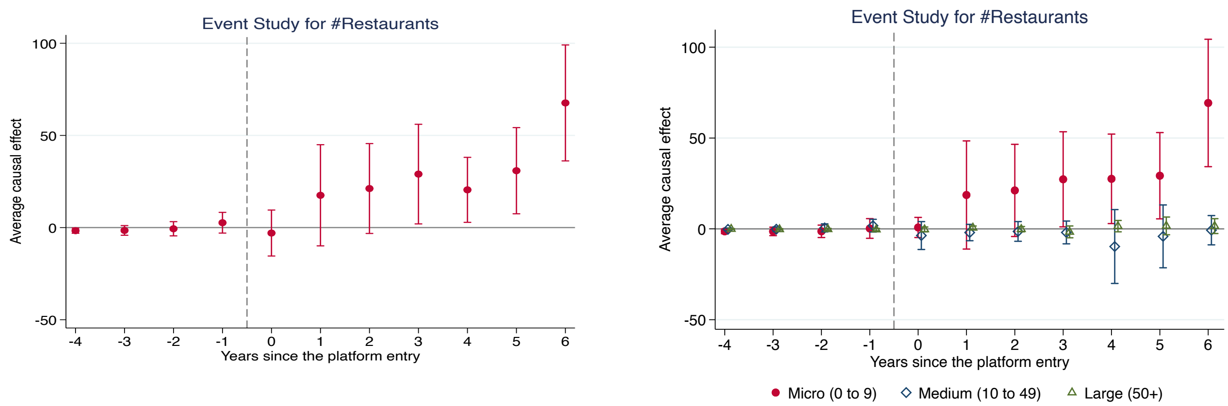
Panel (b) highlights that this growth is driven by independent restaurants, with no significant change observed for chain restaurants, likely due to platforms' ability to provide essential infrastructure, such as delivery logistics and payment processing, which smaller establishments would otherwise struggle to afford. In contrast, establishments already well-known to consumers or firms that already enjoy high levels of brand recognition are less likely to benefit from the broader customer base provision that these technologies provide.

To accommodate zero values in the outcome variable, Equation 1 is specified and estimated in levels (although log transformations are still presented in Figure A17 for reference). However, to enhance interpretability, estimated level effects are converted into percentage changes. This transformation is done by calculating $P_j \equiv \hat{\beta}_j / E[\hat{y}_{st} | t = E_s + j]$, where $\hat{y}_{st}$ is the predicted outcome when omitting the contribution of the event dummies, i.e.,

$$\hat{y}_{st} \equiv \sum_l \hat{\mu}_l \cdot I[l = s] + \sum_k \hat{\lambda}_k \cdot I[k = t].$$

Hence, P_j represents the period-j effect of platform rollout, expressed as a percentage of the outcome that would have occurred without platform presence. This approach follows the methodology used by Kleven *et al.* (2019). As shown in Figure A18, this model reveals a 35% increase in the number of firms.

To assess whether Food Apps disproportionately benefit small restaurants, Figure 6 explores the impact on the number of restaurants by business size, using data from the Inter-Departmental Business Register (IDBR). Unlike LDC data, which relies on field research, the IDBR compiles



(a) Overall **(b)** By Size

Figure 6. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on the total number of restaurants over time. Panel (b) shows the average causal effect on the number of restaurants by size, categorized as micro (0 to 9 employees), medium (10 to 49 employees), and large (50+ employees). The x-axis represents the years since the platform rollout, and the y-axis shows the average causal effect. The data is sourced from an extract compiled from the Inter-Departmental Business Register (IDBR), accessed through NOMIS..

comprehensive business information from administrative sources like VAT and PAYE records, enhancing the validity of our findings. Panel (a) replicates and validates the previous analysis, while panel (b) indicates that smaller businesses, particularly those with fewer employees, experience the most substantial growth following the rollout of food delivery applications. This finding aligns with the notion that these platforms are particularly advantageous for small, independent restaurants, which can leverage the platforms to reach a wider audience without substantial capital investment.

Food Apps account for only a bit more than 10% of total restaurant sales (Figure 1), yet they have caused the number of restaurants to grow by 35%. To reconcile this we have to remember that new restaurants enabled by Food Apps do not necessarily rely exclusively on these platforms. Even a modest additional revenue from Food Apps can make opening a restaurant profitable. Second, and more importantly, Food Apps have led to the proliferation of small restaurants that, while accounting for a small share of sales, greatly contribute to the total number of establishments.

5.1.1. *Consumer Spending Pattern.* Next, I examine how food delivery apps affect consumer spending patterns. A key question is whether consumers simply redistribute their existing spending across more restaurants, or whether food delivery applications stimulate additional spending, thereby expanding the market. The introduction of food delivery applications can create two main substitution effects: customers can either transition from dine-in to delivery, i.e., cross-channel cannibalization, or shift from home cooking to delivery, which expands the market.

To investigate this, I use Kantar's Worldpanel data and apply the same specification as in Equation 1, incorporating individual spending as the outcome variable with individual fixed effects. The results in Figure A22 show that Food App spending increases without reducing other types of restaurant spending. This suggests that the second substitution effect—shifting from home cooking to delivery—is driving the increase.

In other words, food delivery apps expand the overall market. For example, consumers may order delivery during bad weather, a situation in which they might otherwise avoid restaurant spending. This market growth is evident in higher spending in the restaurant industry (and correspondingly higher industry revenues) and an increase in the number of restaurants. It suggests that the effect of reduced barriers to entry dominates any potential superstar impact these platforms might induce.

5.1.2. *Entry and Exit of Restaurants.* The previous analysis shows a net increase in the number of restaurants, but this result may be driven by different patterns of entry and exit. To fully understand how food delivery applications are affecting the market, it is important to look at these two factors separately. An increase in restaurants could come from high rates of new openings and few closures, or from a churn where many restaurants open but also close.

Figure 7 shows that both openings and closures have risen, likely due to heightened competition as food delivery applications expand. Less efficient restaurants may be forced out as consumers have more options and better ways to compare them. However, the number of new openings continues to exceed closures, leading to a net increase in restaurants, particularly among small, independent businesses (Figure A23). This suggests that while some restaurants exit, the reduced barriers to entry provided by food delivery applications—through delivery logistics, marketing, and payment systems—help new entrepreneurs enter the market, more than offsetting the rise in closures.

5.1.3. *Employment.* I examine employment data to see if the increase in restaurants leads to more jobs. For example, employees of large chain restaurants may have left to start their own businesses, "stealing" customers from other establishments, leaving their previous positions unfilled. Higher competition might also push restaurants to cut costs, resulting in more establishments without additional jobs.

Figure A24 shows that employment in the restaurant industry has increased. Panel (a) shows an overall increase in employment, indicating that the rise in the number of restaurants is not driven by the aforementioned scenario but reflects genuine growth in the workforce.

Panel (b) suggests that this growth is even stronger for part-time positions, which aligns with the food delivery industry's need for flexibility. Delivery platforms face sharp demand peaks during mealtimes, while non-platform restaurants experience a steadier customer flow throughout the day as they cater to a broader range of needs. Non-platform restaurants also tend to have more predictable demand due to physical space cap and the deterrent effect of overcrowding, making sudden peaks less likely. These features make part-time workers a better fit for platform restaurants, which offer the flexibility to handle fluctuating order volumes without the long-term commitments of full-time staff.

5.1.4. *Robustness.* I evaluate the stability of the findings through various robustness checks.

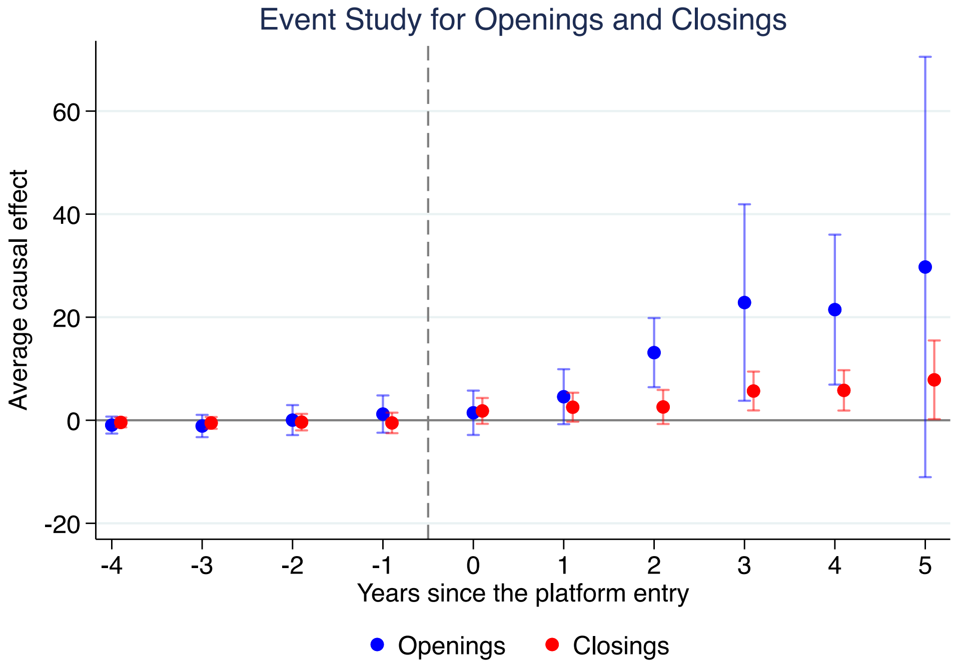


Figure 7. *Notes:* This figure presents the impact of food delivery applications on the number of restaurant closings and opening per year across Local Authority Districts (LADs). The analysis controls for postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

COVID-19. There is also a concern that the COVID-19 pandemic might distort the relationship between platform adoption and outcomes. While the pandemic certainly accelerated platform take-up, this is not necessarily an issue. On the contrary, it can be viewed as a useful force that induced variation in my treatment—food delivery applications. The key question is whether my results are driven by regions that adopted platforms due to COVID-19, and whether these regions are representative of the broader population. To address this, I re-estimate the main analysis without the COVID-19 period. As shown in Figure A19 panel (a), although the estimates become less precise, the magnitude of the effects remains consistent, suggesting that the pandemic does not drive the broader patterns in the data.

Excluding London. London is a unique region with higher restaurant densities and potentially different patterns of platform adoption compared to other areas. To ensure that the results are not disproportionately influenced by dynamics specific to London, I exclude local authorities within London from the analysis. Figure A19, panel (a), shows that the findings remain robust even without London.

Quantile Regressions. A limitation of this level-specification model is that results could be disproportionately influenced by larger values, especially in count outcomes like restaurant numbers, where distributions are often skewed and the mean may not accurately represent the central tendency. If there is impact heterogeneity—meaning the effects vary across different levels of the outcome variable—focusing on mean impacts could mask substantial differences at lower quantiles. To address this, I present quantile regressions of Equation 1, offering insights into the effect of platform rollout across the entire outcome distribution. While these regressions are based on a subsample, leading to somewhat wider confidence bands, the Figure in Appendix A1 demonstrates that median impacts are broadly similar to mean impacts. This finding mitigates the concern that our results are overly reflective of the upper tail of the distribution.

Winsorizing. Outliers in the data can have an outsized influence on regression estimates, particularly in skewed distributions. To address this, I Winsorize the data at the 5th and 95th percentiles, reducing the impact of extreme values. Figure A19, panel (a), demonstrates that the results remain consistent after Winsorization.

Alternative Estimators. To test the sensitivity of the results to different estimation approaches, I re-estimate the model using alternative difference-in-differences estimators, specifically De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). These estimators account for potential variations in treatment effect assumptions. The results, consistent with the main specification, indicate that the platform rollout impacts are robust to changes in the estimation technique.

Placebo Tests with Similar Industries. To validate the exogeneity of the staggered rollout design, Figure A20 presents a placebo test, analyzing the platform's impact on other urban-related industries. No significant effects are found across sectors such as retail, cleaning, and hotels, suggesting the timing of platform rollout is not correlated with other local trends.

Expanded Placebo Tests Across All Industries. To address concerns about cherry-picking placebo industries, Figure A21 expands this test, showing the distribution of t-statistics for all three-digit SIC 2007 industries, with less than 5% of industries showing t-statistics higher than the restaurant sector. These outliers could potentially represent industries benefiting from externalities associated with a growing restaurant presence.

5.2. **Impact on Entrepreneurs: Uneven Entrepreneurial Success Across Demographics.** This section examines which demographic groups benefit the most from food delivery applications. To understand the uneven impact of these platforms, we must first explore the racial dynamics within the restaurant industry. Minorities are heavily represented in the restaurant workforce but their over-representation in the workforce does not seem to translate to entrepreneurship or managerial roles. As shown in Figure A25, although non-White British individuals make up less than 20% of the broader population, they account for nearly 40% of those employed in the restaurant industry. However, their share drops to below 20% in top managerial or ownership positions.[6]

Several factors can explain this disparity, highlighting the unique barriers that minority entrepreneurs face in setting up and owning restaurants. Limited access to finance and capital, often due to a lack of credit history, discrimination by financial institutions, or restricted access to networks, is a major challenge (Fairlie *et al.*, 2022; Bartlett *et al.*, 2022). Additionally, minorities may face discrimination in leasing commercial spaces, with landlords being less willing to rent to them

[6]While our occupation classification does not directly identify ownership, it includes high managerial roles, which also encompass owner-managers.

or offering less favorable terms (Edelman *et al.*, 2017). This discrimination extends to regulatory hurdles and biased interactions with suppliers and customers (Combes *et al.*, 2016; Doleac and Stein, 2013; Leonard *et al.*, 2010). Cultural and language barriers further complicate the business environment, particularly for migrant entrepreneurs (Azmat, 2013; Drori and Lerner, 2002). Navigating the regulatory landscape can be especially challenging for those unfamiliar with local laws and regulations. Furthermore, minority entrepreneurs are often confined to specific industries or market niches, such as ethnic food, where "niche entrapment" might limit their ability to expand into broader markets (Munshi, 2003; Patel and Vella, 2013).

Can Food Apps mitigate these disparities? Potentially, yes. In the theoretical framework, setting up a physical establishment involved uniform fixed cost barriers, while food delivery applications offered lower fixed costs, encouraging more entrepreneurship and leading to the creation of more firms, as observed in previous empirical analyses. However, food delivery applications not only lower fixed costs but also standardize them across demographics, effectively leveling the playing field and disproportionately benefiting those who face higher barriers in the physical setting. By reducing face-to-face interactions, Food Apps can limit discrimination and ease language barriers. They lower fixed costs, alleviating challenges related to raising capital and securing leases. Food Apps also offer broader customer access without the need for extensive marketing, helping minority entrepreneurs overcome traditional network and capital limitations. Integrated payment and logistics services further simplify regulatory navigation.

5.2.1. *Minority Representation in Food Apps.* I begin by presenting descriptive evidence on the representation of restaurateurs from minority backgrounds on food delivery platforms. To do this, I matched data from the Company House directory with scraped data from Deliveroo and UberEats. The matching process is not straightforward due to discrepancies between trading and registered names or addresses. Despite this, I achieved a match quality of around 20%, focusing on matches where I am confident in their accuracy, minimizing false positives. The matching process is detailed in Section A4. Once matched, I inferred the backgrounds of restaurant directors based on their first and last names.

Figure A26 panel (a) shows that minority groups are more represented among restaurants partnered with food delivery applications. While British directors make up 50% of all restaurant directors, their representation drops to 22% in restaurants partnered with Deliveroo and UberEats, reducing to less than. In contrast, minority groups such as Middle Eastern, South Asian, East Asian, and African directors are more prominently represented. This finding is confirmed when analyzing nationality, as shown in panel (b). [7]

[7]There may be concerns that the matched sample of Deliveroo and UberEats restaurants is not representative of all restaurants on these platforms. However, this is unlikely to make minorities overrepresented on the platform; if anything, the opposite may be true. Minority-owned restaurants often use names that reflect their cultural heritage, which may complicate accurate matching using fuzzy algorithms. These names may include uncommon symbols, accented letters, or varying English spellings and transliterations. Furthermore, minority-run businesses, particularly those owned by immigrants, are more likely to operate under trading names that differ significantly from their registered names or to undergo name changes or rebranding as they adjust their business models and update their information. This discrepancy between the names listed on UberEats and those registered with Company House could lead to a lower match rate.

While these descriptive patterns indicate that minorities are overrepresented on food delivery applications, this stylized fact does not imply a causal relationship. It is unclear whether food delivery applications actively increase opportunities for entrepreneurs from underrepresented backgrounds or whether other factors are driving this pattern. For instance, platforms may concentrate on areas with higher minority populations. The next section addresses this question through causal inference methods.

5.2.2. *Food Apps' Impact on Minority Entrepreneurs.* I analyze the causal impact of food delivery applications across demographics of entrepreneurs. To do so, I employ the same dynamic event study framework. However, as I want to report and compare the net effect for entrepreneurs from specific backgrounds, I estimate the average treatment effect over time for different demographic groups. The impact for each demographic group (denoted as g) is estimated using the following equation:

$$y_{g,s,t} = \alpha + \sum_{g} \beta_g D_{st} \times \mathbb{I}(g) + \mu_s + \lambda_t + X_{s,t} \times \lambda_t + \epsilon_{g,s,t} \tag{2}$$

Here, $y_{g,s,t}$ is the number of ethnic group g directors in local authority s at time t, and D_{st} equals 1 if location s is treated at time t (i.e.,$t \geq E_s$). Unlike the previous specification, which estimates separate coefficients for multiple leads and lags, this approach focuses on a single coefficient, capturing the average effect over time for each demographic group. This choice allows me to report and compare net effects across groups more directly.

Figure 8 reveals significant variation in the platform's impact on different backgrounds, with entrepreneurs with African and Middle-Eastern-sounding names benefiting the most. This suggests that food delivery applications are effective in democratizing market access for immigrant entrepreneurs, providing them with a viable pathway to business ownership and success. I also examine the impact based on nationality. Figure A27 shows that immigrant entrepreneurs from the Middle East and Africa benefit the most, while European and British entrepreneurs benefit the least.

I further analyze the impact on entrepreneurs by gender and age. Appendix Figure A28 panel (a) shows no significant difference between female and male entrepreneurs. Panel (b) reveals that while the platforms offer opportunities across all ages, the impact diminishes for older age groups. This suggests that younger people, who may face more barriers in traditional restaurant operations while also having higher digital literacy, benefit from the platforms. Interestingly, there is also a significant but noisy positive impact on the 60+ age group, hinting at a U-shaped relationship where both younger entrepreneurs with digital skills and older entrepreneurs with experience or capital gain the most.

5.3. **Impact on the Product Market: Enhancing Cuisine Diversity.** In this section, I examine whether the observed democratization of restaurant entrepreneurship extends to the product market, specifically affecting cuisine diversity and consumer options. To this end, I examine which cuisine types benefit most from Food Apps and how this affects cuisine diversity.

Figure 8. *Notes:* The figure shows the impact of the platform on different background groups, reported as the percentage changes by computing $\Delta\hat{y}_m = \hat{\beta}_m / E(\hat{y_m}|D_{it} = 1)$, where $E(\hat{y_m}|D_{it} = 1)$ is the average predicted number of entrepreneurs from background m after the rollout of the platform when omitting the contribution of the treatment variable for the presence of the platform. The analysis controls for location and year-fixed effects, as well as local economic indicators and population interacted by time. Backgrounds are determined by inferring ethnicities from the first and last names of individuals using data from Company House.

First, I provide descriptive evidence on the cuisine types of app-partnered restaurants. I compare restaurants on Food Apps to those not listed to examine differences in cuisine types. Using LDC data, I categorize restaurants by cuisine type based on specific keywords and match them with UberEats and Deliveroo listings. I use only trusted matches to ensure conservative estimates with a low false-positive rate. Figure A26 panel (c) shows that non-UK cuisine types are more prevalent among app-partnered establishments. This observation is not necessarily causal; it may reflect a greater inclination of non-UK cuisine restaurants to join these platforms rather than Food Apps directly causing the creation of minority cuisine establishments.

To measure the causal impact of food apps on each cuisine type, I use the same research design based on the staggered rollout specified in Equation 2, but now the outcome variable is the number of restaurants offering a specific cuisine. I also follow the same technique and normalize the results by the predicted value of the outcome variable in the absence of treatment to estimate percentage changes in the number of restaurants specializing in each cuisine.

Figure 9 demonstrates substantial heterogeneity in the impact of food apps across different cuisine types, indicating that these platforms do not benefit all cuisines equally. (The corresponding

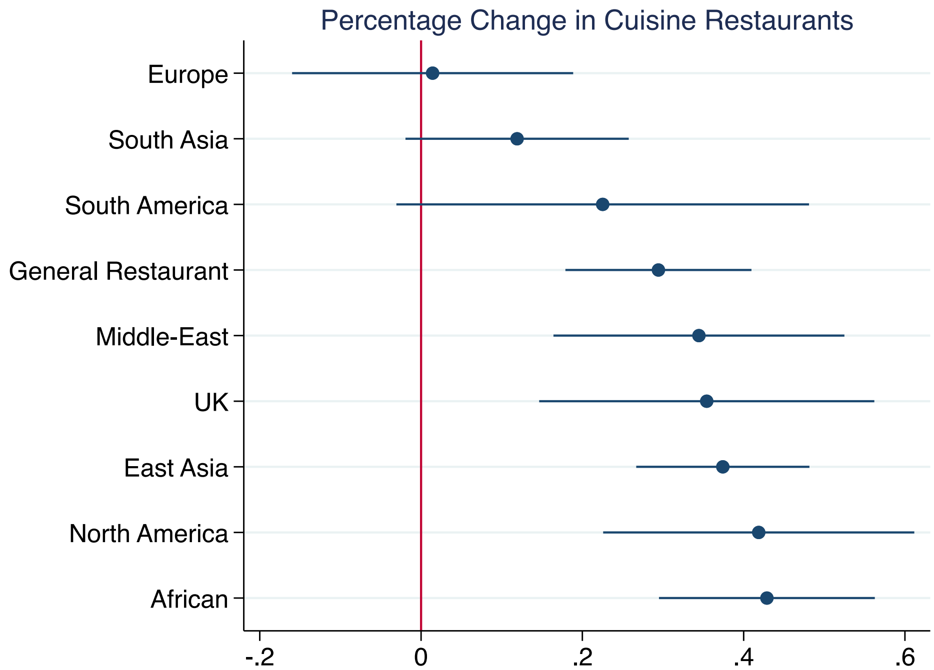


Figure 9. *Notes:* The figure shows the impact of the platform on different cuisine types, reported as the percentage changes by computing $\Delta\hat{y}_m = \hat{\beta_m}/E(\hat{y_m}|D_{it} = 1)$, where $E(\hat{y_m}|D_{it} = 1)$ is the average predicted number of cuisine m restaurants after the rollout of the platform when omitting the contribution of the treatment variable for the presence of the platform. The analysis controls for location and year-fixed effects, as well as local economic indicators and population interacted by time. Cuisine types are categorized as outlined in Table A8. Data is sourced from Companies House.

results in levels are provided in Appendix Figure A35.) Interestingly, the variation in cuisine benefits partially corresponds to the patterns seen in entrepreneur demographics in Figure 8. For instance, cuisines from African and Middle Eastern regions benefit significantly, much like the entrepreneurs from these areas, while European cuisines and entrepreneurs show comparatively smaller effects.

To explore the reasons behind this pattern, I consider the concept of homophily. In the context of entrepreneurship, this implies that entrepreneurs may choose to offer cuisines that match their cultural backgrounds. This might be because individuals from a particular region have a comparative advantage in establishing restaurants that serve their native cuisine, due to specialized knowledge, skills, and cultural capital. Such comparative advantage arises from possessing specific human capital, including cooking techniques, traditional recipes, and cultural understanding. If Food Apps disproportionately assist underrepresented groups, and if homophily holds, we would expect a wider variety of cuisines available to consumers.

5.3.1. *Homophily.* I start by showing the distribution of different cuisine types, inferred from Google Maps, based on the entrepreneurs' backgrounds inferred from their names on the Company House.

Figure A34 shows that restaurant directors are more likely to offer cuisines that align with their own backgrounds. For example, more than 50% of Middle Eastern restaurants are run by people with Middle Eastern-sounding names while only close to 10% of them have white-sounding names.

To quantify the extent of this homophily, I conduct regression analyses. The specification is as follows:

$$y_{i,g} = \alpha_g + \beta_g \times \mathbb{I}\left[i \in g\right] + \epsilon_{i,g}, \quad \forall g$$

In this equation, $y_{i,g}$ is a dummy variable indicating whether the restaurant director i belongs to the group g, and $\mathbb{I}\left[i \in g\right]$ is a binary variable indicating whether the restaurant's cuisine corresponds to the group g. I run this regression for each background group. The directors' backgrounds are inferred from Companies House data, while the restaurant's cuisine type is based on Google Maps listings. I also perform this separately for the subset of directors of app-partnered restaurants.

The results, shown in Figure 10, reveal positive coefficients across all groups, confirming homophily among all demographics. Some groups exhibit stronger correlations; for instance, South Asian restaurants are 30% more likely to have a director with a South Asian-sounding name. Interestingly, the degree of homophily seems to be stronger for overall restaurants compared to those on food delivery applications [8].

5.3.2. *Cuisine Diversity.* To determine whether the heterogeneous impact across cuisine types leads to greater overall diversity, I employ different measures to quantify the diversity of restaurant offerings within postal districts over time. These measures are designed to capture both the concentration and the variety of cuisine types available to consumers.

First, I calculate the Herfindahl-Hirschman Index (HHI) to assess the market concentration of different cuisine types within each spatial unit and time period. In the absence of revenue or sales data that has information on the cuisine type, I use the proportion of restaurants belonging to each cuisine type as a proxy for market share. The HHI is computed using the formula:

$$\text{HHI}_{st} = \sum_{i=1}^{K_{st}} \left(\frac{n_{ist}}{N_{st}} \right)^2$$

where n_{ist} is the number of restaurants of cuisine type i in postal district s at time t, $N_{st} = \sum_{i=1}^{K_{st}} n_{ist}$ is the total number of restaurants in postal district s at time t, and i indexes the different cuisine types, ranging from 1 to K.

A higher HHI indicates greater concentration (less diversity), while a lower HHI suggests a more diverse culinary landscape within the postal district. I define cuisine types at two levels of

[8] There might be several reasons for this. First, in traditional restaurants, face-to-face interactions make having a background that aligns with the cuisine type crucial for creating authenticity and signaling expertise, something missing in the online framework. Second, traditional brick-and-mortar restaurants typically attract customers from their local neighborhoods, with the surrounding area's ethnic composition influencing the types of restaurants that succeed. In contrast, food delivery applications weaken the tie between location and clientele, allowing them to serve diverse audiences beyond their local ethnic communities.

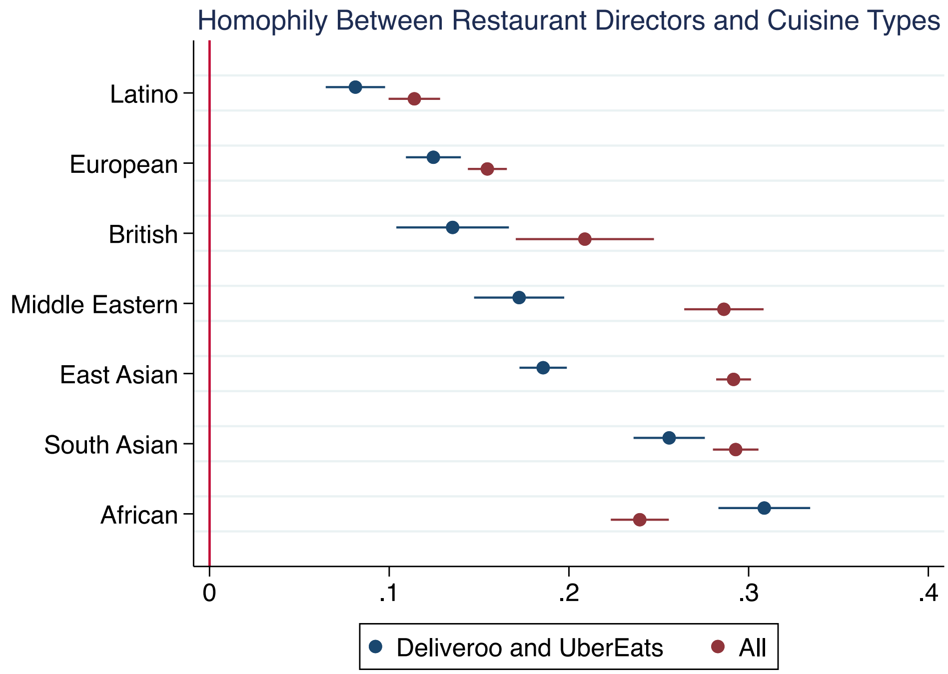


Figure 10. *Notes:* This figure illustrates the degree of homophily between restaurant directors and the cuisine type of their restaurant. Directors' backgrounds are inferred from their first and last names as described in the text, using data from Companies House. Restaurants listed in Companies House are matched to Google Maps based on name and postcode, with cuisine type inferred from Google Maps information. The probability of a director having a Muslim background is linked to Middle Eastern cuisines, and the probability of having a Hispanic background is linked to South American cuisines. Probabilities of having European and East Asian probabilities are the maximum values derived from subcategories (e.g., various European nationalities, East Asian, and Japanese), based on name analysis.

granularity—for example, one broad category like "Indian" and another more specific, such as "South Asian.".

Second, I calculate the number of distinct cuisine types present in each spatial unit and time period. This measure is defined as:

$$D_{st} = \left|\left\{i \;\middle|\; n_{ist} > 0\right\}\right|$$

where the notation $|\cdot|$ denotes the size of the set, and the set $\left\{i \;\middle|\; n_{ist} > 0\right\}$ includes all cuisine types i for which there is at least one restaurant in spatial unit s at time t. This measure provides a straightforward count of the variety of cuisine types, offering insight into the breadth of options available to consumers. I calculate this measure using both granular and broader classification.

Using the same research design as before, I now consider each of the four measures of cuisine diversity as the outcome variable. Table 1 presents the results for both levels of categorization.

Table 1. Platform and Diversity, Postal District Analysis

	Broad Cuisine Categories		Detailed Cuisine Categories	
	HHI (Cuisine)	#Cuisine Types	HHI (Cuisine)	#Cuisine Types
FDP	-0.022	0.174	-0.021	0.422
	(0.004)	(0.033)	(0.004)	(0.066)
Mean of dep. variable	.339	4.89	.215	11.9
Location FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Spatial units	2050	2052	2050	2052
Observations	26745	28728	26745	28728

Notes: This table presents the impact of food delivery applications (FDP) on cuisine diversity at the postal district level, measured using different diversity metrics. The columns show results for both broad and detailed cuisine categories, using the Herfindahl-Hirschman Index (HHI) for cuisine concentration and the number of cuisine types. The analysis controls for location and year fixed effects, as well as local economy indicators interacted by time. Broad cuisine types are categorized as outlined in Table A8. Data is sourced from the Local Data Company (LDC).

The findings indicate that the rollout of food delivery applications leads to an increase in cuisine diversity across all metrics: the HHI decreases, and the number of distinct cuisine types increases.

5.3.3. *Robustness.* A potential concern with the disproportionate benefit of food delivery applications for ethnic minority cuisines is that the observed relationship may be driven by demographic shifts, with platforms expanding in already diverse regions that are attracting more migrants. This could suggest a spurious correlation rather than a causal effect. To address this, I perform two analyses. First, I restrict the sample to British nationals, who are either born in the UK or have lived there for many years, to ensure that the increase in minority cuisines is not simply due to new migration. The results remain consistent, indicating that the rise in minority cuisines is not tied to recent demographic changes. Second, I conduct a placebo analysis by examining spending on items from grocery stores indicative of specific cuisine types, such as falafel for Middle Eastern cuisine or curry for South Asian cuisine. If the demographic shifts were driving the observed increase in restaurant cuisine types, we would expect to see a similar effect. However, as Figure A36 shows, there is no significant correlation between platform rollout and spending on these items.

5.4. **Mechanisms Behind Differential Entrepreneurial Impact.** I explore why food delivery applications disproportionately benefit minority entrepreneurs. While I cannot empirically test each mechanism individually, I provide evidence on key factors that may drive these outcomes.

There are two main reasons why minorities might benefit more. The first mechanism aligns with the theoretical framework presented earlier, where setting up a physical establishment involves uniform fixed costs for all entrepreneurs. In this framework, food delivery applications reduce these fixed costs equally for everyone. Under this mechanism, minorities might have been less productive or less able to cover the high fixed costs in the past, and the lowering of these costs now allows them to enter the market.

The second mechanism involves the idea that different demographics face different levels of fixed costs in traditional settings. Minority entrepreneurs may have faced higher barriers than others, but they were not less productive. Food delivery applications not only lower fixed costs but also harmonize them across demographics, effectively leveling the playing field. That is, if the costs associated with digital platforms are more evenly distributed across backgrounds compared to traditional restaurant costs, then delivery platforms promote a more equitable business landscape across diverse demographics.

Each explanation has different policy implications. The first suggests a need for policies focused on improving productivity among minority entrepreneurs through training and resources. The second implies that policies should focus on removing structural barriers and reducing discrimination that lead to higher barriers for minorities.

To investigate these hypotheses, I focus on three key areas of evidence. First, I analyze restaurant productivity to assess whether minority-run restaurants are less productive, which assesses the first mechanism. Second, I examine the racial composition of customers to explore whether changes in customer demographics contribute to the benefits minorities receive, shedding light on potential reductions in discrimination and face-to-face biases. Third, I assess the impact in less expensive versus more expensive parts of the same neighborhood to see if operating in more affordable locations explains the disproportionate benefits to minorities. This considers whether capital constraints and difficulties in securing prime locations hindered minority entrepreneurs before. Both the second and third pieces of evidence relate to the second mechanism, where food delivery applications reduce and harmonize barriers that previously disadvantaged minorities. Lastly, I discuss a potential alternative mechanism involving the reduction of search frictions in the product market.

5.4.1. *Productivity.* I measure restaurant productivity using average Google reviews. I infer whether a restaurant is minority-run by matching listings to Companies House data, and I determine platform presence by matching to platform listings. While Google reviews are not perfect measures of productivity, they are the best available, as they capture consumer satisfaction and can be linked to entrepreneurs' backgrounds and platform presence.

Table A6 shows that minority-run restaurants on food delivery apps are not less productive than others. Specifically, the results from Column (3) indicate that minority-run restaurants on food delivery apps do not exhibit significantly lower productivity, compared to either minority-run restaurants not on the app or non-minority-run restaurants on the app. The interaction term (Minority $\times$ Food App) of 0.11 offsets much of the review penalty associated with minority ownership (-0.16) and app presence (-0.13). This suggests that minority-run restaurants on food delivery apps perform similarly to their counterparts.

5.4.2. *Racial Composition of Consumers.* To determine whether food delivery applications help minority-run restaurants overcome barriers or biases in face-to-face interactions, I analyze the racial composition of customers. If food apps mitigate such biases, we might expect minority-run or ethnic cuisine restaurants to attract a different racial composition of customers, particularly reaching more white customers.

For this analysis, I utilize a dataset of over 6 million Google Reviews left on UK restaurants. Google Reviews provide a rich source of customer feedback and include reviewer names, which I use to infer racial backgrounds. Additionally, by identifying platform-specific keywords in the reviews, I can determine whether an order was placed through a food delivery application. The result of the racial inference of customers depends on the demographic composition of reviewers and their propensity to leave reviews. While the tendency to leave reviews might vary among different ethnic groups, it is unlikely to differ systematically across different cuisine types within each ethnic group.

First, I conduct a non-parametric analysis to compare the racial distribution of customers across app-partnered and non-partnered restaurants. I find that the racial makeup of customers remains consistent across app-partnered and non-partnered restaurants, as well as between Food App and offline customers of app-partnered establishments, regardless of the ethnic cuisine offered. Figure A29 illustrates this non-parametrically, with the bars showing the racial profile of customers for non-partnered restaurants, app-partnered restaurants, and a subset of app-partnered restaurant customers confirmed to have placed orders through Food Apps.

To further investigate this issue, I perform a parametric analysis focusing specifically on white customers. To ensure a clear distinction between the two cases, I include reviews from restaurants not on the platform and reviews from app-partnered restaurants where the order is explicitly linked to a food delivery application. I regress an indicator variable for whether the reviewer is white on a set of dummy variables for different cuisine types and interaction terms between these cuisine types and an indicator for reviews associated with platform orders. The regression specification is as follows:

$$W_{ir} = \alpha + \sum_k \beta_k \text{CuisineType}_k + \sum_k \gamma_k (\text{CuisineType}_k \times \text{PlatformOrder}_i) + \epsilon_{ir}$$

where W_{ir} is an indicator variable equal to 1 if reviewer i of restaurant r is inferred to be white, CuisineType_k are dummy variables for each cuisine type k, PlatformOrder_i is an indicator variable equal to 1 if the review includes keywords suggesting it is about an order placed through the platform. Coefficients γ_k in this specification allow me to test whether the likelihood of a reviewer being white differs for platform orders compared to orders for restaurants that are not on the platform, across various cuisine types. A positive and significant coefficient on the interaction terms would indicate that platform orders are associated with a higher proportion of white customers for ethnic cuisines.

The results indicate that the interaction terms γ_k are generally insignificant or, in some cases, negatively significant. This indicates that there is no evidence to suggest that food delivery applications help ethnic cuisine restaurants attract more white customers. For instance, the argument that Food Apps allow minorities to overcome face-to-face racial biases—by attracting customers who might otherwise avoid visiting their establishments in person—is not supported by this evidence. Also, the notion that Food Apps enable minority-run restaurants to enter predominantly white neighborhoods, which they might otherwise avoid, seems unlikely given the consistent racial makeup of users across platforms.

Therefore, the benefit to minority entrepreneurs is not from reaching different racial groups. Minority-run restaurants probably reach a wider geographic customer base using food apps, but not a different demographic one.

5.4.3. *Differential Effects in Low-Cost Areas.* I examine whether Food Apps allow entrepreneurs to open restaurants in cheaper, more deprived areas while still reaching customers. This option may have been less feasible in traditional settings.

To compare the net effect across different levels of physical space price within the same postal district, I divide each postal district into four units based on the quartile of the property price index and estimate the following equation:

$$y_{s,j(s),t} = \alpha + \sum_{j=1}^{4} \beta_j D_{st} \times \mathbb{I}\left[j(s) = j\right] + \mu_s + \lambda_t + X_s \times \lambda_t + \epsilon_{s,j(s),t} \tag{3}$$

Here, $y_{s,j(s),t}$ represents the number of restaurants in postal district s, quartile $j(s)$ of postal district s, at time t. D_{st} is an indicator variable equal to 1 if the area had access to the food delivery application at time t.

Figure 11 highlights the differential impact of food delivery application rollouts on restaurant numbers across various price level quartiles within the same postal district for White British vs non-White British. The largest increase—over 100%—occurs in the least expensive areas for non-White British entrepreneurs. For White British entrepreneurs, the impact is negligible, except for a positive effect in the most expensive areas.

A likely explanation is that minority entrepreneurs often face credit constraints and higher barriers to entry in high-rent areas. Food Apps reduce the need for prime locations, allowing restaurants to operate in lower-cost areas without losing access to customers. This enables minority entrepreneurs, who may have less capital, to open businesses with lower fixed costs. This explains why non-White British entrepreneurs see a larger positive impact in less expensive areas.[9]

While the within-district analysis highlights the tendency for businesses to cluster in cheaper areas within a postal district, I also examine the broader effects across entire postal districts, treating each district as a single unit. Figure A33 confirms that the impact is stronger in cheaper districts and those with lower IMD levels. Combined, these findings indicate that Food Apps facilitate restaurant openings in both cheaper districts and the least expensive areas within districts.

5.4.4. *Alternative Mechanism: Reduction in Search Frictions.* An alternative explanation for the increase in cuisine diversity is that food delivery applications reduce search costs for consumers, directly impacting the product market. In traditional settings, consumers face high search costs

[9]To address the limitations of Company House data, which excludes unincorporated businesses and uses registered addresses, I supplement it with LDC data, which includes both incorporated and unincorporated businesses and focuses on trading addresses. However, LDC lacks information on director ethnicity and cannot distinguish results for minority versus non-minority groups. Figure A32 shows stronger effects in cheaper neighborhoods and areas with lower IMD levels within postal districts.

Figure 11. *Notes:* This figure illustrates the average causal effect of food delivery application rollout on the demographics of entrepreneurs categorized as White British and non-White British, across different land price quartiles within postal districts. The x-axis represents land price quartiles, while the y-axis shows the average causal effect in percentage terms. The estimation is based on the specification in 3, controlling for postal district and year fixed effects, as well as local economic indicators and population trends interacted with time. The data is sourced from Companies House, covering the period from 2010 to 2023.

when seeking products that match specific preferences, especially niche or minority-preferred products like ethnic cuisines. Digital food delivery applications lower these search frictions by providing a centralized marketplace where consumers can easily find and evaluate a wide array of culinary options. Thus, platforms increase the visibility and accessibility of niche cuisines. This aligns with the "long tail" effect in the literature (Brynjolfsson *et al.*, 2006, 2011), which suggests that reducing search frictions disproportionately benefits niche products by connecting them with consumers who have specific tastes.

This mechanism suggests that the platforms first enhance the product market by making niche cuisines more accessible. As a result, entrepreneurs who specialize in these cuisines—often ethnic minorities—benefit from increased demand and choose to enter the market. Thus, the impact on entrepreneurs is a consequence of the initial effect on the product market.

Disentangling this mechanism from the reduction in the entry barrier effect discussed in this paper is challenging due to homophily—the tendency of individuals to produce goods aligned with their cultural backgrounds, which I documented. Because entrepreneurs often offer cuisines that reflect their heritage, any change in the product market naturally correlates with changes in the entrepreneurial landscape. This interdependence makes it difficult to determine whether the primary driver is reduced search frictions for consumers or lowered entry barriers for entrepreneurs.

Despite this complexity, several factors suggest that reduced search frictions are a less likely primary driver in this context. First, many cuisines that benefited from food apps, such as East Asian and British cuisines (Figure 9), are not niche in the UK, as shown by their prevalence (Figure A26, Panel (c)). Second, looking at where the product market and entrepreneurial impacts diverge uncovers an important insight. For instance, while British cuisine benefits modestly from platform expansion, White British entrepreneurs do not experience similar gains. If reduced search costs were the primary driver, the growth in British cuisine should lead to more opportunities for White British entrepreneurs. Instead, the benefits accrue disproportionately to ethnic minority entrepreneurs, even within British cuisine. This divergence implies that the platforms are specifically helping minority entrepreneurs, rather than changes in consumer search behavior alone.

Therefore, although I cannot fully rule out the alternative mechanism and acknowledge that both effects may coexist, the evidence points toward the reduction of entry barriers for minority entrepreneurs as the more significant factor. The platforms enable these entrepreneurs to overcome traditional obstacles, leading to increased representation in the market and a corresponding rise in the supply of ethnic cuisines.

6. Conclusion

Food delivery applications exemplify a broader shift in business and employment structures offered by digital marketplaces. This shift is characterized by lowered entry barriers that democratize market access, but it also introduces mechanisms that could lead to superstar effects. This paper delves into how these digital marketplaces influence the restaurant industry, particularly in democratizing market access. At the firm level, I find that these platforms reduce entry barriers, leading to an increase in restaurant numbers, driven by the entry of small, independent businesses. At the entrepreneur level, the most significant benefits are seen among minority and migrant entrepreneurs. For the product market, this democratization results in greater cuisine diversity, offering consumers a wider range of choices.

Why do minority entrepreneurs benefit more? It is not because minorities are less productive and only enter when barriers are low; the evidence indicates that minority-run restaurants on these platforms are just as productive as their counterparts. Instead, the key factor is that digital marketplaces not only reduce but also standardize and harmonize entry barriers. Thus, groups that face more challenges in traditional settings—like credit constraints—gain the most.

To understand the mechanisms behind this phenomenon, I examine whether reaching new customer demographics contributes to the benefits received by minority entrepreneurs. Analysis of the racial composition of customers shows no significant changes, suggesting that platforms do not primarily help minorities by expanding their customer base to different racial groups. Instead, the evidence indicates that platforms enable minority entrepreneurs to overcome the high costs of securing prime property locations. Food delivery apps make it viable for them to operate in lower-cost areas within the same neighborhoods, consistent with the notion that they face challenges in the brick-and-mortar context, such as credit constraints.

The results presented in this paper should be interpreted cautiously for several reasons. Firstly, my estimates are relatively short-term. On the consumer side, currently, younger, wealthier users drive food delivery application growth, but as other demographic groups adopt these services, their preferences could shift. For example, they might substitute food delivery for dine-in options, potentially reducing its overall impact. On the platform side, platforms may gradually achieve monopolistic positions, potentially altering their interactions with both restaurant owners and users.

Furthermore, this study does not capture the overall welfare effects of food delivery applications. A comprehensive assessment would need to consider various dimensions, including potential benefits such as reducing time spent on food preparation, supporting new work arrangements like working from home and creating employment opportunities for couriers, as well as potential downsides like health impacts.

How generalizable are these findings to other digital marketplaces? Restaurants, with their short life cycles and unregulated spatial patterns, are highly sensitive to urban changes, making them ideal for studying the economic impact of digital platforms. However, limitations exist. First, the two forces examined—lowered entry barriers and superstar effects—may behave differently elsewhere. While reduced entry barriers are common across digital marketplaces, the level of market integration varies. In food delivery, restaurants compete locally due to the perishable nature of the product. This explains why, despite some exits from the market, the reduction in entry barriers outweighs these exits, leading to a net increase in restaurants. In contrast, digital marketplaces like Amazon or Google Play involve national or global competition, potentially allowing a few large firms to dominate and limiting the benefits of lower entry barriers for smaller businesses. Second, the link between entrepreneurship and product diversity may be less direct in other contexts. In the restaurant industry, homophily ensures that increased minority entrepreneurship leads to more diverse offerings. This connection may be weaker on platforms like Amazon or Google Play, where products are less likely to reflect the backgrounds of entrepreneurs.

How can policymakers promote entrepreneurship, especially among underrepresented groups? This research demonstrates that the digital marketplace plays a pivotal role in transforming the food service industry by reducing entry barriers and fostering entrepreneurship. To harness these benefits, policymakers should focus on increasing digital literacy and providing the necessary infrastructure to ensure access to these platforms. Investing in secure and uninterrupted internet connectivity is particularly relevant for developing countries. Finally, addressing the specific challenges of traditional settings remains essential to creating a more equitable entrepreneurial landscape.

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Appendix A1. Quantile Treatment Effects

In this section, I describe the application of a non-linear Difference-in-Differences (DiD) method to estimate the impact of the platform rollout on the distribution of the number of restaurants across different regions. The resulting Quantile Treatment Effects (QTEs) enable us to assess the impact on different parts of the outcome distribution.

Before delving into our results, it is helpful to briefly review the concepts of quantiles and QTEs. For any variable Y with a CDF function $F(y) \equiv \Pr[Y \leq y]$, the qth quantile of F is defined as the smallest value y_q such that $F(y_q) = q$. In a purely random treatment setting, we could compare two distributions, F_1 and F_0, representing the outcome variable in the treatment and control groups, respectively. The QTE at the qth quantile is then defined as $\Delta_q = y_q(1) - y_q(0)$, where $y_q(t)$ is the qth quantile of distribution F_t. This effect can graphically be represented as the horizontal distance between the graphs of F_1 and F_0 at the probability value q.

It is crucial to recognize that QTEs do not necessarily identify the treatment's impact on a specific locality or neighborhood. For example, if the platform leads to rank reversals in the distribution of restaurant numbers, simply knowing the median differences between the two distributions will not suffice to calculate the treatment effect for a locality that would have had the median number of restaurants either before or after the treatment. Nevertheless, the presence of a negative (positive) QTE indicates that the treatment effect is negative (positive) across some non-degenerate interval of the counterfactual restaurant distribution.

The inclusion of covariates and fixed effects complicates the analysis by necessitating a choice between conditional and unconditional quantile regression.[10] In conditional quantile regression (CQR), the inclusion of fixed effects controls for selection bias but also alters the definition of quantiles. That is, CQR estimates the treatment's impact on the nth conditional quantile of the outcome variable, indicating how the policy affects those at specific positions within the distribution of the outcome variable, conditional on the covariates or fixed effects. However, our primary interest lies in understanding the impact on units with low outcome levels unconditionally. Unconditional quantile regression (UQR) addresses this by estimating the effect of the policy on the overall distribution of the outcome variable, providing insights more relevant for policy evaluation. Unlike CQR, which focuses on within-group effects, UQR captures the impact of the independent variable on the entire distribution of the dependent variable, akin to OLS regression.

Unconditional quantile regression (UQR) offers the advantage of defining quantiles prior to model estimation, making it less susceptible to influence from right-hand-side variables. However, computational challenges arise when applying UQR to models with high-dimensional fixed effects. To address this, the recentered influence function (RIF) method is employed. This involves calculating Influence Function (RIF) for each observation and subsequently using these as the dependent variable in an OLS regression with the relevant independent variables. For a detailed

[10] It is important to note that when no other covariates are involved, the conditional and unconditional treatment effects of a binary X are the same across all quantiles of Y. However, once additional covariates, such as fixed effects, are introduced—as in our study—the distinction between conditional and unconditional quantile regression becomes significant.

methodological explanation, refer to Firpo *et al.* (2009). UQR estimates offer a more intuitive interpretation compared to conditional quantile regression, as they capture the impact of the treatment on specific quantiles of the outcome without conditioning on other variables or within groups, as in conditional quantile regression.

Figure A37 displays the QTE estimates derived from the RIF-DiD estimator. The point estimates are either zero or positive across the distribution up to the 92nd percentile. As we move to higher quantiles, particularly between the 70th and 80th percentiles, the QTE becomes more positive, peaking around the 80th percentile. However, confidence intervals widen significantly at higher quantiles, suggesting greater uncertainty or heterogeneity in treatment effects at the upper end of the distribution.

Overall, the QTE estimates suggest that the introduction of food delivery applications had a positive impact across most of the distribution of the number of restaurants. However, it is important to interpret these results with caution. To the best of my knowledge, within the context of quantile regression in a Difference-in-Differences framework with staggered treatment rollout, there is no established package that fully addresses the complexities of treatment effect heterogeneity, as highlighted by Borusyak *et al.* (2024), and the challenges of conditional quantile regression with many fixed effects. Consequently, this analysis may not fully account for the concerns raised by the treatment heterogeneity literature. This is particularly important given the potential heterogeneity in treatment effects across markets of different sizes on the one hand and the relationship between treatment timing and the initial market conditions on the other.

Appendix A2. Extracting Restaurants on Google Maps

This section details the methodology employed to extract and analyze data on restaurants listed in the UK using the Google Maps API. The objective was to comprehensively capture all restaurants within the UK and gather detailed information about each establishment.

To cover the entire UK, a bounding box was defined with the southwest corner at 49.9°N, 7.5°W and the northeast corner at 59.0°N, 2.0°E. Then, a grid of coordinates was generated to cover the entire bounding box by selecting alternating points in a checkerboard pattern. This technique ensures complete coverage, preventing gaps through balanced overlap while reducing excessive redundancy.

For each location in the grid, I used the Google Maps Places API (`nearbysearch`) to search for restaurants within the specified radius. The issue is that the API limits the number of returned restaurants results per request, so I implemented a recursive mechanism to handle this issue.

The API returns a maximum of 60 results per request for a set of restaurants within a specified radius. If exactly 60 restaurants are returned, it indicates that there may be more restaurants in the area that were not retrieved in this call. To address this, smaller grids centered around the current location were defined recursively, narrowing down the search area until all restaurants were fetched. This approach ensured no restaurants were missed in densely populated areas.

After obtaining the initial list of restaurants, the Google Maps Place Details API (`details`) was used to fetch additional information for each establishment using `place_id`. This step provided detailed attributes such as business status, delivery options, types of meals served, reviews, and geolocation. The API response was parsed to extract relevant attributes including postcode, administrative level, country, business status, and geolocation.

Retrieving Permanently Closed Restaurants: When using broad searches (e.g., nearby searches), Google tends to prioritize showing operational businesses. This means permanently closed restaurants are not likely to show up using the method described before. However, when performing a very specific text search, Google may return the place along with its closure status if it is available. To achieve this, I use historical Food Hygiene Ratings lists to get a list of restaurants in the UK, including names and geolocations. For each restaurant in this historical data, I use the `findplacefromtext` method of the Google Places API to search for the restaurant by name and location.

Identifying the Earliest Review Date: The Google API provides up to five reviews per restaurant, which is insufficient for demographic analysis on the set of cusomers. To capture the full set of reviews, I employed manual web scraping techniques, allowing me to retrieve the earliest review date for each restaurant.

Appendix A3. Name-Based Analysis to Infer Ethnicity and Gender

As described, the company house dataset lacks direct information on gender and ethnicity. However, these attributes can be inferred using name-based analysis. This approach, widely used in research economics and economic history (Kerr, 2008; Gaulé and Piacentini, 2013; Abramitzky *et al.*, 2024), employs an algorithm or machine learning methods to predict race and ethnicity based on names. For this purpose, the `ethnicolr` Python package is utilized, a tool increasingly common in academic literature (Anginer *et al.*, 2020; Parasurama, 2020; Bologna Pavlik and Zhou, 2023).

The `ethnicolr` package uses a long short-term memory (LSTM) neural network trained on US census data, Florida voter registration data, and Wikipedia data (Sood and Laohaprapanon, 2018). This study uses the model trained on Wikipedia, as it is less US-centric compared to other datasets. LSTM networks, a type of recurrent neural network (RNN) introduced by seminal work of Graves and Schmidhuber (2005), are particularly effective due to their unique memory cells that selectively remember and forget information, allowing for efficient incremental updates.

Using the Wikipedia training dataset compiled by Ambekar *et al.* (2009), `ethnicolr` predicts race and ethnicity based on first and last names. The package achieves higher accuracy when both first and last names are used together, as this provides more comprehensive information (Sood and Laohaprapanon, 2018). Although the training dataset is not specific to the UK, its global scope likely covers a wide range of immigrant backgrounds relevant to the UK. Hafner *et al.* (2023) showed Wikipedia-trained `ethnicolr` has shown a more balanced performance across ethnicities compared to other methods.

Technically, `ethnicolr` calculates the probability that a given name belongs to one of thirteen racial/ethnic groups: "Asian, Greater East Asian, East Asian", "Asian, Greater East Asian, Japanese", "Asian, Indian Subcontinent", "Greater African, Africans", "Greater African, Muslim", 'Greater European, British", "Greater European, East European", "Greater European, Jewish", 'Greater European, West European, French", "Greater European, West European, Germanic", "Greater European, West European, Hispanic", "Greater European, West European, Italian", and "Greater European, West European, Nordic". These categories are further classified into British, South Asia, East Asia, European, South American, Muslim, and African.

To infer genders from names in my dataset, I utilize the `gender-guesser` package. This package allows me to determine the likely gender associated with a given first name through a straightforward Python interface. By inputting names into the package, I can classify each as male, female, androgynous (andy), mostly male, mostly female, or unknown if the name is not found in the underlying database. For analysis, I treat "mostly male" as male and "mostly female" as female, as this does not significantly impact the results. The process involves creating a Detector object from the package, which uses a precompiled list of over 40,000 names and their associated genders and countries of origin. This dataset is designed to encompass the majority of first names used in European countries and several non-European countries, including China, India, Japan, and the US. By leveraging this tool, I can systematically infer and categorize the genders of individuals in my dataset, facilitating comprehensive demographic analysis.

Appendix A4. Matching Restaurants Across Datasets

Matching restaurants across different data sources, such as LDC, Google Maps, and delivery platforms, is complicated by inconsistencies in business names, address variations, and chain restaurants with multiple locations.

To achieve accurate matches, I employed a multi-step methodology combining exact matches with fuzzy matching techniques. Initially, I identified chain restaurants using a predefined list and matched them based on exact business names and postcodes. For non-chain or unmatched entries, I leveraged fuzzy matching based on restaurant names within the same postal district to account for minor discrepancies in naming conventions.

Specifically, I used the `fuzzywuzzy` library's `extractOne` function for this fuzzy matching. This tool compares a given restaurant name with a list of possible matches, calculating a similarity score based on Levenshtein distance, which measures how many single-character edits are needed to make the names identical. The function returns the closest match along with a similarity score ranging from 0 to 100.

If the similarity score was above 80, I accepted the match. For scores between 70 and 80, I further verified the match by checking exact postcode matches within the same postal district. This hybrid approach maximized accuracy and ensured a comprehensive understanding of market presence and business dynamics while accounting for variability in business records.

Appendix A5. Model Details

A5.1. **Utility Function and Consumer Preferences.** The first part of the model refers to consumer preferences and utility maximization under monopolistic competition:

$$\max\ U = \left[\int_{\Omega} \left(q(\omega)^{\frac{\sigma-1}{\sigma}}\right) d\omega\right]^{\frac{\sigma}{\sigma-1}}$$

Where:

- U is the utility of the representative consumer.
- Ω is the set of available varieties (goods).
- $q(\omega)$ is the quantity consumed of variety ω.
- σ is the elasticity of substitution between varieties (with $\sigma > 1$).

The first-order condition (FOC) of utility maximization leads to the demand for each variety:

$$q(\omega) = YP(\omega)^{-\sigma}P^{\sigma-1}$$

Where P is the aggregate price index, defined as:

$$P = \left(\int_{\Omega} P(\omega)^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}$$

There are L identical consumers:

$$y(\omega) = Lq(\omega) = LwP(\omega)^{-\sigma}P^{\sigma-1}$$

Where w is the wage rate which can be set to one.

A5.2. **Production: Monopolistic Competition.** The firm maximizes its profit under monopolistic competition:

$$\max_{\{q\}}\ \pi = pq - C(q)$$

From the firm's pricing rule and profit maximization:

$$P + \frac{dP}{dq}q - C = 0 \quad \Rightarrow \quad P(1 + \frac{dP}{dq}\frac{q}{P}) = C$$

This leads to the condition:

$$p(1 - \frac{1}{\epsilon_q}) = C \quad \text{or} \quad \frac{P}{C} = \frac{\epsilon_q}{\epsilon_q - 1}$$

Where ϵ_q is the price elasticity of demand. So, we can write:

$$P(\phi) = \frac{\sigma}{\sigma-1}\frac{w}{\phi}$$

Where ϕ represents the firm's productivity. Revenue is given by:

$$r(\phi) = LP^{\sigma-1}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left(\frac{\phi}{w}\right)^{1-\sigma}$$

The profit function is:

$$\pi(\phi) = y(\phi)r(\phi) - y(\phi)\frac{w}{\phi} - wf_d = \frac{r(\phi)}{\sigma} - wf_d$$

Which simplifies further into:

$$\pi(\phi) = LP^{\sigma-1}\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma}\left(\frac{\phi}{w}\right)^{\sigma-1} - wf_d$$

Where f_d is the fixed cost of production.

A5.3. **Zero-Profit Cutoff Condition.** The profit condition for firms is given by:

$$\pi_d(\varphi^*) = YLP^{\sigma-1}\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma}\frac{\varphi^{*\sigma-1}}{w^{\sigma-1}} - wf_d = B_p\varphi^{*\sigma-1} - wf_d = 0$$

Where $B_p = LP^{\sigma-1}\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma w^{\sigma-1}}$

At the survival cutoff φ^*, profits are driven to zero:

$$B_p\varphi^{*\sigma-1} = wf_d$$

A5.4. **Free Entry Condition.** The free entry condition requires that the expected profit from entering the market equals the entry cost wf_e:

$$wf_e = \int_{\varphi^*}^{\infty}\pi(\phi)dG(\phi)$$

Where $G(\phi)$ is the distribution of firm productivities. Substituting the profit function:

$$wf_e = \int_{\varphi^*}^{\infty}\left(B_p\phi^{\sigma-1} - wf_d\right)dG(\phi)$$

If we substitute for B_p and set wage to one, this becomes:

$$wf_e = \int_{\varphi^*}^{\infty}\left(f_d\left(\frac{\phi}{\varphi^*}\right)^{\sigma-1} - f_d\right)dG(\phi) = f_d\int_{\varphi^*}^{\infty}\left(\left(\frac{\phi}{\varphi^*}\right)^{\sigma-1} - 1\right)dG(\phi)$$

Assuming a Pareto distribution for ϕ with scale parameter ϕ_{min} and shape parameter θ, the integral can be expressed in a closed-form solution. By substituting the probability density function (PDF) into the integral, we obtain:

$$I = \int_{\varphi^*}^{\infty}\left(\left(\frac{\phi}{\varphi^*}\right)^{\sigma-1} - 1\right)\frac{\theta\,\phi_{\text{min}}^\theta}{\phi^{\theta+1}}\,d\phi$$

We simplify the integrand by separating the terms:

$$
\begin{aligned}
I &= \theta\,\phi_{\min}^{\theta}\left[\int_{\varphi^*}^{\infty}\left(\frac{\phi}{\varphi^*}\right)^{\sigma-1}\frac{1}{\phi^{\theta+1}}\,d\phi-\int_{\varphi^*}^{\infty}\frac{1}{\phi^{\theta+1}}\,d\phi\right]\\
&= \theta\,\phi_{\min}^{\theta}\left[\varphi^{*-(\sigma-1)}\int_{\varphi^*}^{\infty}\phi^{\sigma-\theta-2}\,d\phi-\int_{\varphi^*}^{\infty}\phi^{-\theta-1}\,d\phi\right]\\
&= \theta\,\phi_{\min}^{\theta}\left[\varphi^{*-(\sigma-1)}\left(-\frac{\varphi^{*\sigma-\theta-1}}{\sigma-\theta-1}\right)-\frac{\varphi^{*-\theta}}{\theta}\right]\\
&= \theta\,\phi_{\min}^{\theta}\left[-\frac{\varphi^{*-(\sigma-1)}\varphi^{*\sigma-\theta-1}}{\sigma-\theta-1}-\frac{\varphi^{*-\theta}}{\theta}\right]\\
&= \theta\,\phi_{\min}^{\theta}\left[-\frac{\varphi^{*-\theta}}{\sigma-\theta-1}-\frac{\varphi^{*-\theta}}{\theta}\right]\\
&= \phi_{\min}^{\theta}\varphi^{*-\theta}\left[-\frac{\theta}{\sigma-\theta-1}-1\right]\\
&= \left(\frac{\varphi^*}{\phi_{\min}}\right)^{-\theta}\left(\frac{\sigma-1}{1+\theta-\sigma}\right)
\end{aligned}
$$

setting wage equal to one, this would imply:

$$
\varphi^* = \phi_{\min}\left(\frac{f_d}{f_e}\right)^{\frac{1}{\theta}}\left(\frac{\sigma-1}{1+\theta-\sigma}\right)^{\frac{1}{\theta}} \tag{4}
$$

A5.5. **Proofs.** *Proposition I Proof* The labor market equilibrium can be expressed as:

$$
L = M_a\int_{\phi_a}^{\infty}\left[\frac{Lq(\phi)}{\phi}+f_d\right]\frac{g(\phi)}{1-G(\phi_a)}d\phi+M_e f_e
$$

We know that $M_e=\frac{M_a}{1-G(\phi_a)}$

$$
L = M_a\int_{\phi_a}^{\infty}\left[\frac{Lq(\phi)}{\phi}+f_d\right]\frac{g(\phi)}{1-G(\phi_a)}d\phi+M_a\frac{f_e}{1-G(\phi_a)}
$$

Using the relationship for labor demand:

$$
\frac{Lq(\phi)}{\phi}+f_d=\frac{Py(\phi)}{W}-\frac{\pi(\phi)}{W}=(\sigma-1)\frac{\pi(\phi)}{W}+\sigma f_d
$$

Substituting this into the labor market equilibrium condition, we have:

$$
\begin{aligned}
L &= M_a\int_{\phi_a}^{\infty}\left[(\sigma-1)\frac{\pi(\phi)}{W}+\sigma f_d\right]\frac{g(\phi)}{1-G(\phi_a)}d\phi+M_a\frac{f_e}{1-G(\phi_a)}\\
L &= M_a\left[(\sigma-1)\frac{\bar{\pi}}{W}+\sigma f_d\right]+M_a\frac{f_e}{1-G(\phi_a)}\\
L &= M_a\left[(\sigma-1)\frac{f_e}{(1-G(\phi_a))W}+\sigma f_d\right]+M_a\frac{f_e}{1-G(\phi_a)}
\end{aligned}
$$

Finally, solving for M_a:

$$M_a = \frac{L}{\sigma\left(\frac{f_e}{1-G(\phi_a)} + f_d\right)}$$

This expression gives the equilibrium number of active firms M_a as a function of total labor, the fixed costs, and the productivity distribution cutoff ϕ_a.

Assuming Pareto distribution for ϕ, we have $1 - G(\phi_a) = \left(\frac{\phi_{\min}}{\varphi^*}\right)^\theta$. Substituting the value of φ^* from equation 4, this becomes $\frac{f_e}{f_d}\frac{1+\theta-\sigma}{\sigma-1}$. Using this relationship, we can express the equilibrium mass of active firms as:

$$M_a = \frac{L}{\sigma \; f_d \frac{\theta}{1+\theta-\sigma}} = \frac{L\left(1+\theta-\sigma\right)}{\sigma f_d \theta} \tag{5}$$

From this expression, we observe that M_a increases with θ. This implies that if a technology enhances the productivity of superstar firms—resulting in a decrease in θ (i.e., making the productivity distribution more fat-tailed)—the mass of active firms in the market decreases. □

Proposition II Proof From the labor market equilibrium equation (Equation 5), it is evident that a decrease in f_d leads to an increase in the mass of firms. □

Proposition III Proof Starting from the expression for the equilibrium mass of active firms:

$$M_a = \frac{L(1+\theta-\sigma)}{\sigma f_d \theta}$$

Treating L and σ as constants, we can write M_a as a function of θ and f_d:

$$M_a = \frac{C(1+\theta-\sigma)}{f_d\theta} \quad \text{where} \quad C = \frac{L}{\sigma}$$

To find how M_a changes with θ and f_d, we compute the total differential dM_a:

$$dM_a = \frac{\partial M_a}{\partial \theta} d\theta + \frac{\partial M_a}{\partial f_d} df_d$$

Calculating the partial derivatives:

$$\frac{\partial M_a}{\partial \theta} = \frac{C\left[(\theta)(1) - (1+\theta-\sigma)(1)\right]}{f_d\theta^2} = \frac{C(\sigma-1)}{f_d\theta^2}$$
$$\frac{\partial M_a}{\partial f_d} = -\frac{C(1+\theta-\sigma)}{f_d^2\theta}$$

Substituting back into the total differential:

$$dM_a = \frac{C(\sigma-1)}{f_d\theta^2} d\theta - \frac{C(1+\theta-\sigma)}{f_d^2\theta} df_d$$

To express the changes in proportional terms, we divide both sides by M_a:

$$
\begin{aligned}
\frac{dM_a}{M_a} &= \left(\frac{1}{M_a}\right)\left(\frac{\partial M_a}{\partial \theta}d\theta + \frac{\partial M_a}{\partial f_d}df_d\right) \\
&= \left(\frac{f_d\theta}{C(1+\theta-\sigma)}\right)\left(\frac{C(\sigma-1)}{f_d\theta^2}d\theta - \frac{C(1+\theta-\sigma)}{f_d^2\theta}df_d\right) \\
&= \frac{(\sigma-1)}{\theta(1+\theta-\sigma)}d\theta - \frac{df_d}{f_d}
\end{aligned}
$$

Recognizing that $d\theta$ and df_d are negative due to decreases in θ and f_d, we let:

$$d\theta = -\Delta\theta \quad \text{and} \quad df_d = -\Delta f_d$$

Substituting back:

$$\frac{dM_a}{M_a} = -\frac{(\sigma-1)}{(1+\theta-\sigma)}\frac{\Delta\theta}{\theta} + \frac{\Delta f_d}{f_d}$$

For the equilibrium number of firms to increase ($dM_a > 0$), we require:

$$\frac{\Delta f_d}{f_d} > \frac{(\sigma-1)}{(1+\theta-\sigma)}\frac{\Delta\theta}{\theta}$$

This condition ensures that the positive effect of reduced fixed costs outweighs the negative effect of a more unequal productivity distribution. □

The Impact on the Price index:

We have:

$$YLP^{\sigma-1}\frac{(\sigma-1)^{(\sigma-1)}}{\sigma^\sigma}\varphi^{*\sigma-1} = f_d$$

We can see that if φ^* increases, P has to decrease.

Appendix A6. Analysis of Restaurateurs' Experiences on Reddit

To gain insights into the motivations and experiences of restaurant owners regarding the adoption of food delivery applications, I collected data from two Reddit subreddits: `r/restaurateur` and `r/restaurantowners`. These forums serve as platforms where restaurant owners and prospective owners discuss industry-related topics, share experiences, and seek advice.

I extracted all posts from these subreddits that contained keywords indicative of food delivery applications, such as "UberEats", "Deliveroo", "food delivery app", "Grubhub", and "DoorDash." The time frame for data collection spanned from January 2015 to December 2023, capturing the period during which food delivery applications became prominent in the industry.

Traditional text analysis methods, such as Latent Dirichlet Allocation (LDA), often require extensive preprocessing and may not capture nuanced language used in informal online discussions. To address these limitations, I employed Large Language Models (LLMs) to analyze the collected Reddit posts. Specifically, I utilized OpenAI's GPT series models, known for their advanced natural language understanding capabilities.

The analysis proceeded in two main stages:

1. Topic Identification and Classification Scheme Development. I randomly sampled 100 posts from the dataset to serve as a representative subset for initial analysis. Using the GPT-4 model (version `OpenAI's GPT-o1`), I performed a qualitative content analysis to identify recurring themes and topics within these posts. From this analysis, I identified several key topics, which formed the basis of the classification scheme. The primary categories included:

(1) **Expanding Customer Reach**
(2) **Marketing and Visibility**
(3) **Operational Efficiency and Workflow Infrastructure**
(4) **Reducing On-Premise Delivery Costs**
(5) **Reducing Premises Costs**
(6) **Competitive Pressure**
(7) **Customer Convenience**
(8) **Data and Analytics Access**

2. Automated Classification of the Full Dataset. With the classification scheme established, I proceeded to classify the entire dataset of posts using the GPT-4 model (`gpt-4o-2024-08-06`). The process involved feeding each post into the LLM with instructions to assign one or more of the predefined categories based on the content of the post. Posts were allowed to be assigned multiple categories if they touched on several topics. To assess the reliability of the LLM's classifications, I compared the automated classifications with manual annotations on a random subset of 50 posts, achieving an agreement rate of over 90%, which indicates high consistency. Discrepancies between the automated and manual classifications were analyzed to refine prompts and improve the model's performance.

The prompt used was:

"Read the following post from a restaurant owner discussing food delivery applications. If the post discusses the possibility of joining a food delivery application, expresses interest in joining, or mentions benefits of using such platforms, identify and list the main reasons they mention for adopting or considering the use of these platforms from the following list..."

Results. The classification results are summarized in Figure A5. The most frequently cited reason for adopting food delivery applications was **Expanding Customer Reach**, highlighting the importance restaurant owners place on accessing a broader market.

Other significant motivations included:

- **Marketing and Visibility (18.2%)**: Restaurant owners appreciated the promotional benefits provided by the platforms, which reduce the need for independent marketing efforts.
- **Operational Efficiency and Workflow Infrastructure (17.6%)**: The platforms' integrated order management and delivery logistics streamline operations, lowering the burden on in-house staff.
- **Reducing On-Premise Delivery Costs (13.1%)**: Outsourcing delivery services to the platforms eliminates the need to maintain a fleet of delivery personnel.
- **Reducing Premises Costs (7.4%)**: Some restaurant owners noted that partnering with delivery apps allows them to operate in smaller physical spaces or less expensive locations, as dine-in facilities become less critical.

Appendix A7. Determinants of Platform Rollout Dates

I employ a basic machine learning approach to identify the subsets of regional factors that most effectively predict the platform's rollout dates accross UK postal districts. Although my goal is not to establish a causal explanation due to the multifaceted nature of platform decisions, an in-depth examination of various socio-economic variables can shed light on the elements influencing the system's rollout, which serves as the identifying variation in this study.

More concretely, I conduct a feature selection procedure to determine the strongest predictors of the rollout date. FFor this, I apply Best Subset Selection (BSS), a machine learning method used for feature selection, aimed at reducing the dimensionality of the feature space. The concept behind BSS is to test all possible models, considering every combination of control variables, and produce the statistically best-fit model that minimizes an information criterion. The detailed steps are as follows:

A7.1. **Covariates Selection.** I consider covariates that pass a first plausibility test. If this test is not satisfied, the model may include variables lacking theoretical justification, practical relevance, or empirical support, leading to several issues. These issues include compromised interpretability, reduced predictive accuracy and reliability due to noise, and overlooked multicollinearity causing unstable coefficients.

The covariates I choose include variables from groups such as indicators of the area's restaurant industry, variables reflecting the trend in demographic and human capital characteristics, and metrics that capture the region's economic structure and its evolution. More specifically, there are more than 30 variables used in this analysis, including both level and trend variables. These variables represent aspects such as population size, number of restaurants, GDP, urbanization levels, age demographics, hourly pay statistics, migration growth, unemployment rates, and economic dependence on various sectors, migration growth, unemployment rates, and sectoral employment shares in agriculture, mining, manufacturing, construction, retail, hotel and restaurant, transport, and finance. These variables capture both the current state and the changes in regional socio-economic conditions.

A7.2. **Best Subset Identification.** BSS involves evaluating all possible combinations of predictors to find the subset that best fits the data for different numbers of parameters. Initially, models containing a single predictor ($p = 1$) are evaluated, with each model assessed for its fit using metrics like the residual sum of squares (RSS). Next, all possible models containing exactly two predictors ($p = 2$) are evaluated. This step involves assessing the fit of models with pairs of predictors. The process continues for models with three predictors, four predictors, and so on, until all combinations of predictors have been considered. This exhaustive search ensures that the best subset of predictors is identified for each possible number of parameters.

$$\min_{\beta} \sum_{c=1}^{C} \left(y_c - \beta_0 - \sum_{j=1}^{p} x_{cj}\beta_j \right)^2 \quad \text{Residual sum of squares}$$

Once I have the total set of covariates, BSS evaluates all possible combinations of predictors and selects the subset that minimizes a specific criterion. In this analysis, I use the commonly employed Akaike Information Criterion (AIC).

A7.3. **Information Criterion.** The previous step helps to find the best predictors for each number of predictors. The information criterion refines the model selection by providing a criterion for choosing the best model among the subsets of predictors. The AIC balances model fit and complexity, ensuring that the selected model is not only accurate but also parsimonious.

More formally, the objective is to minimize the AIC for each subset of predictors S:

$$\min_{S \subseteq \{1,2,\ldots,p\}} \left\{ n \ln\left(\frac{\text{RSS}(S)}{n} \right) + 2|S| \right\}$$

where:

- $\text{RSS}(S) = \sum_{i=1}^{n} \left(y_i - \sum_{j \in S} \beta_j X_{ij} \right)^2$
- $|S|$ is the number of predictors in the subset S
- n is the number of observations

Using AIC in BSS ensures that the selected model not only fits the data well but also remains parsimonious, avoiding the pitfalls of overfitting.

This statistically optimal approach can quickly become impractical as the number of potential regressors, p, increases. In BSS, the process involves estimating models for every possible combination of regressors using Ordinary Least Squares (OLS). Initially, models with one regressor are evaluated, followed by models with two regressors, and so on, until all combinations are considered. This results in evaluating 2^p models in total. As p grows, the computational burden becomes immense, making the process infeasible for large datasets. While our model had just enough potential features to remain feasible, larger sets of features necessitate the use of regularization methods like LASSO and Ridge Regression. These methods solve convex optimization problems efficiently, making them suitable for high-dimensional data.

One should bear in mind that the BSS method can generate models with varying levels of complexity, which are not necessarily nested. I outline the sequence of 'best' models for each set of predictors p and assess how including additional covariates enhances the model's fit. A drawback of this approach is that highly correlated variables may be excluded. This implies that even if a predictor x_i provides a unique contribution when conditioned on x_j, it might be left out of the analysis if its signal isn't strong enough.

A7.4. **Results.** Table A9 presents the results of the BSS analysis. The first column reports the model that includes only the best predictor. The second column adds the best when we can have two predictors, and so forth, with each subsequent column incorporating an additional permissible predictor. As evident from the results, rurality emerges as the most significant predictor, followed by population size and educational attainment. Notably, trend variables do not seem to play a significant role in predicting platform rollout dates. This indicates that while certain static socio-economic factors are critical, rather than underlying trends. It is worth highlighting that the R^2 is overall high.

A7.5. **Shorrocks-Shapley Decomposition:** After using BSS to select the best subset of predictors, the Shorrocks-Shapley decomposition (Shorrocks, 2013) can be applied to the final model to understand the relative contribution of each selected predictor to the R^2. The Shorrocks-Shapley decomposition works by considering all possible permutations of the predictors and calculating the marginal contribution of each predictor to the R^2 of the model. This marginal contribution is the change in R^2 when a predictor is added to a model that includes a subset of the other predictors. By averaging these marginal contributions across all possible orderings of the predictors, the Shorrocks-Shapley value for each predictor is obtained.

Figure A38 shows the results. As you can see Urbanisation, population and GDP level are the most important contributors to predicting the rollout date.

Appendix A8. Graphs

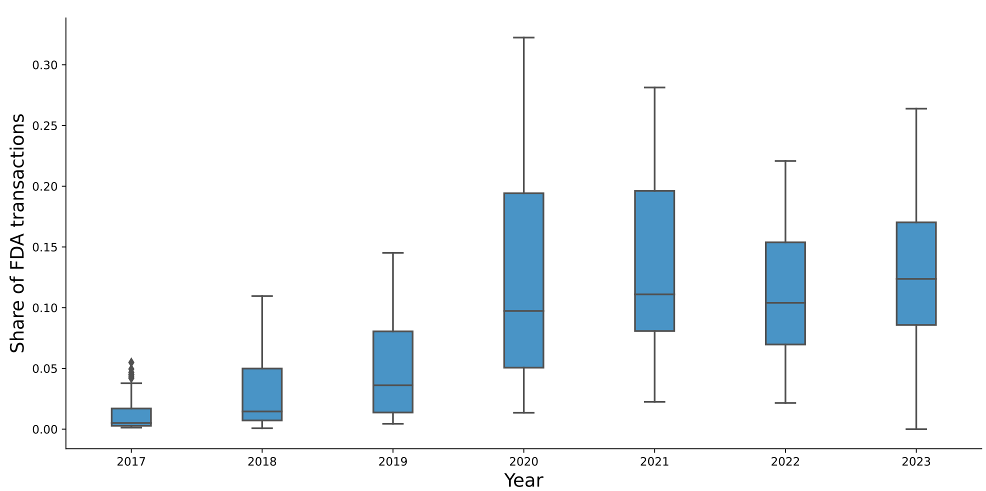


Figure A1. *Notes:* The figure shows a box-and-whisker plot depicting the penetration of UberEats and Deliveroo across ONS subgroups over time. The y-axis represents the share of Food App transactions, while the x-axis shows the years from 2017 to 2023. Data reflects the distribution and trends in the adoption of these platforms over the specified period.

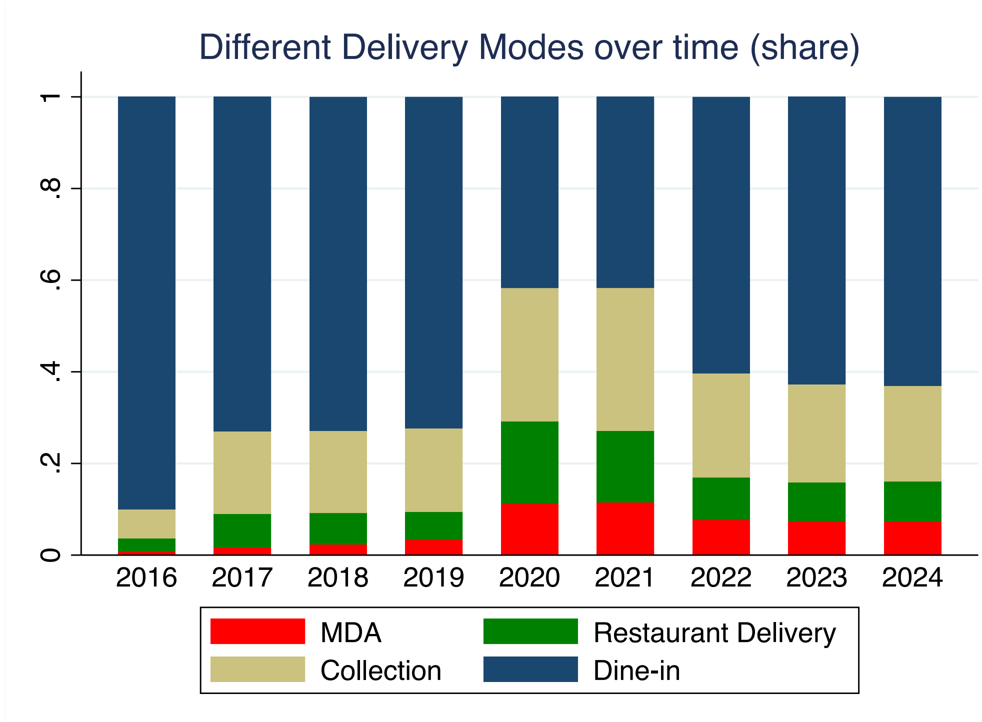
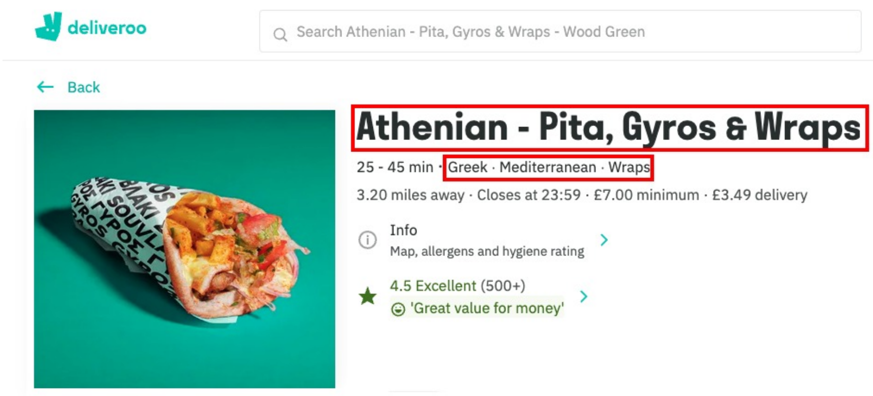
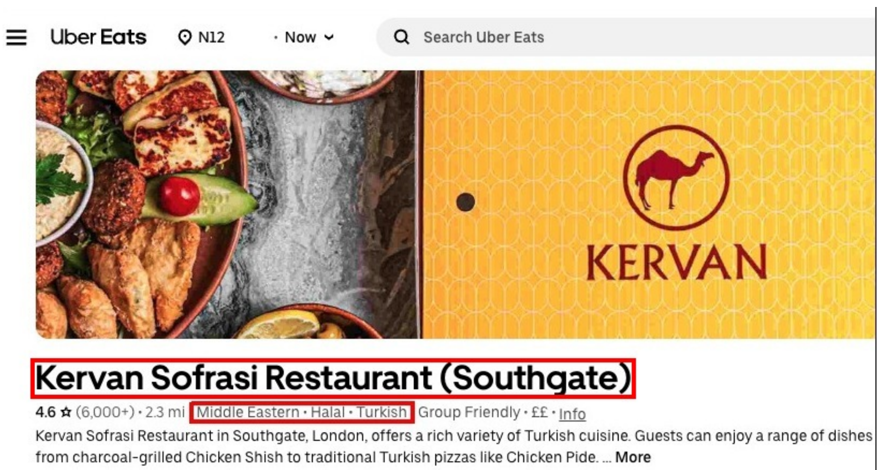


Figure A2. *Notes:* The graph depicts the distribution of delivery modes over time. The first category includes dine-in orders. The second category encompasses orders made through food delivery applications from services Just Eat, Uber Eats, Deliveroo, Amazon Restaurants, and Hungry House. This category also includes orders placed through these platforms for personal collection. The third category represents orders delivered by the restaurant's own fleet, placed either through the restaurant's application, website or via phone. The final category is for customers who personally visit the restaurant to pick up their food. The data is from Kantar's Worldpanel Out of Home Panel for the years 2016 to 2024 Q1. It is important to note that orders labeled a "Restaurant's Own Website" (approximately 0.19% of observations) are assumed to involve delivery, though this label does not explicitly distinguish between delivery and collection. The graph is constructed based on observations where mealcomponent==1 thus excluding drinks and side dishes only transactions. It excludes data from years before 2017, as there are no recorded deliveries for those years.

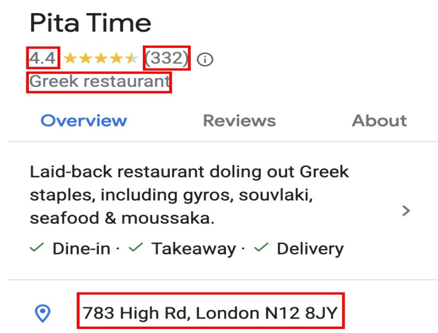


(a) Deliveroo

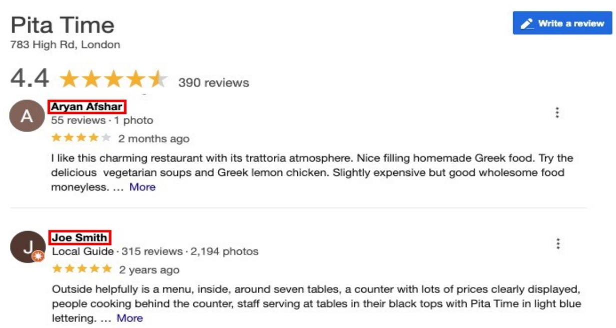


(b) UberEats

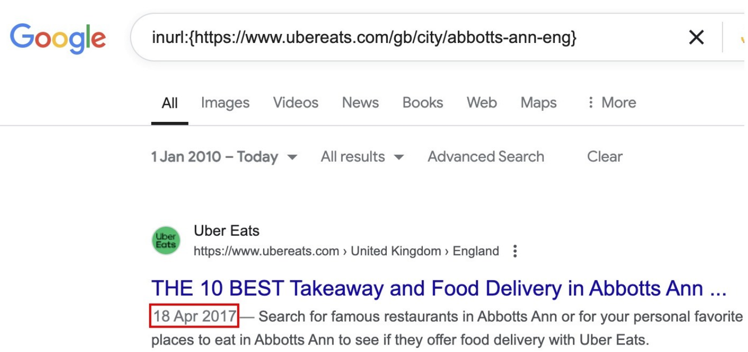
Figure A3. *Notes:* Panel (a) shows a sample restaurant on Deliveroo along with key information extracted from it, such as the name, rating, cuisine type, and address. Panel (b) displays the same procedure for a restaurant on UberEats.



(a) Google Maps



(b) Google Reviewers



(c) Google Indexed date

Figure A4. *Notes:* This figure presents a sample of information extracted from Google Maps. Panel (a) shows a restaurant listing with key details, such as rating, cuisine type, and address. Panel (b) displays sample reviewers for the restaurant. In practice, all reviews for each restaurant are scraped, and reviewers' names are extracted to infer their backgrounds. Panel (c) shows a Google search result for a location's UberEats URL, with the indexed date indicated.

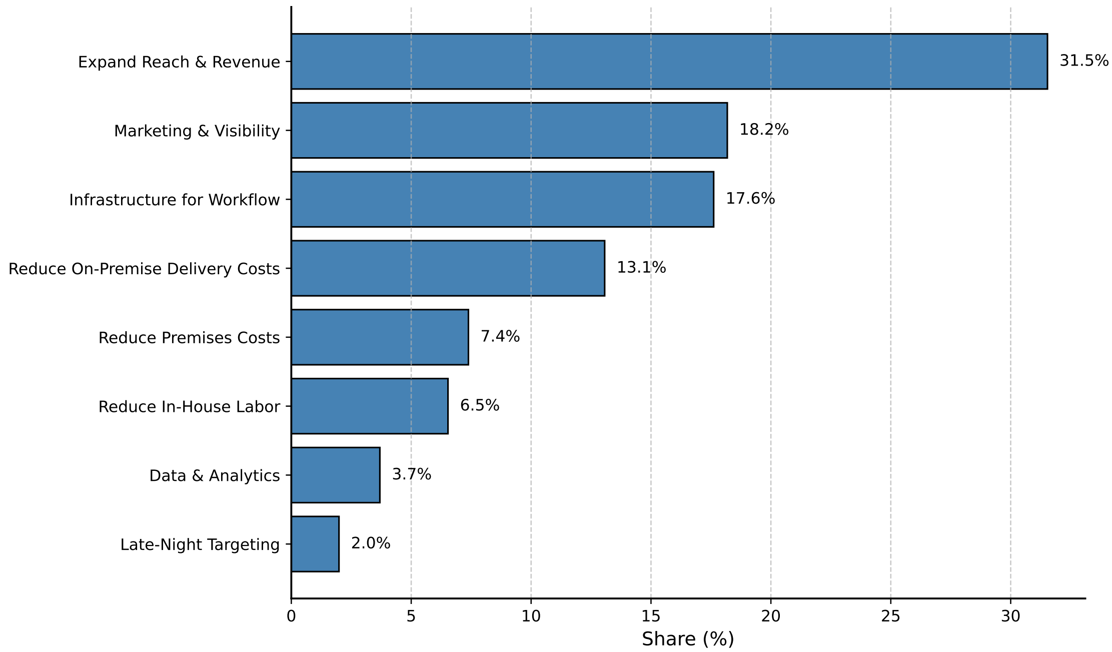


Figure A5. *Notes:* This figure illustrates the percentage distribution of identified reasons why restaurateurs consider partnering with food delivery apps, based on data from Reddit's `r/restaurateur` and `r/restaurantowners` subreddits. Posts mentioning relevant keywords indicative of using food apps (661 posts) were aggregated and analyzed using OpenAI's GPT-4 language model (`gpt-4o-2024-08-06`), which classified each post according to a set of predefined benefit categories.

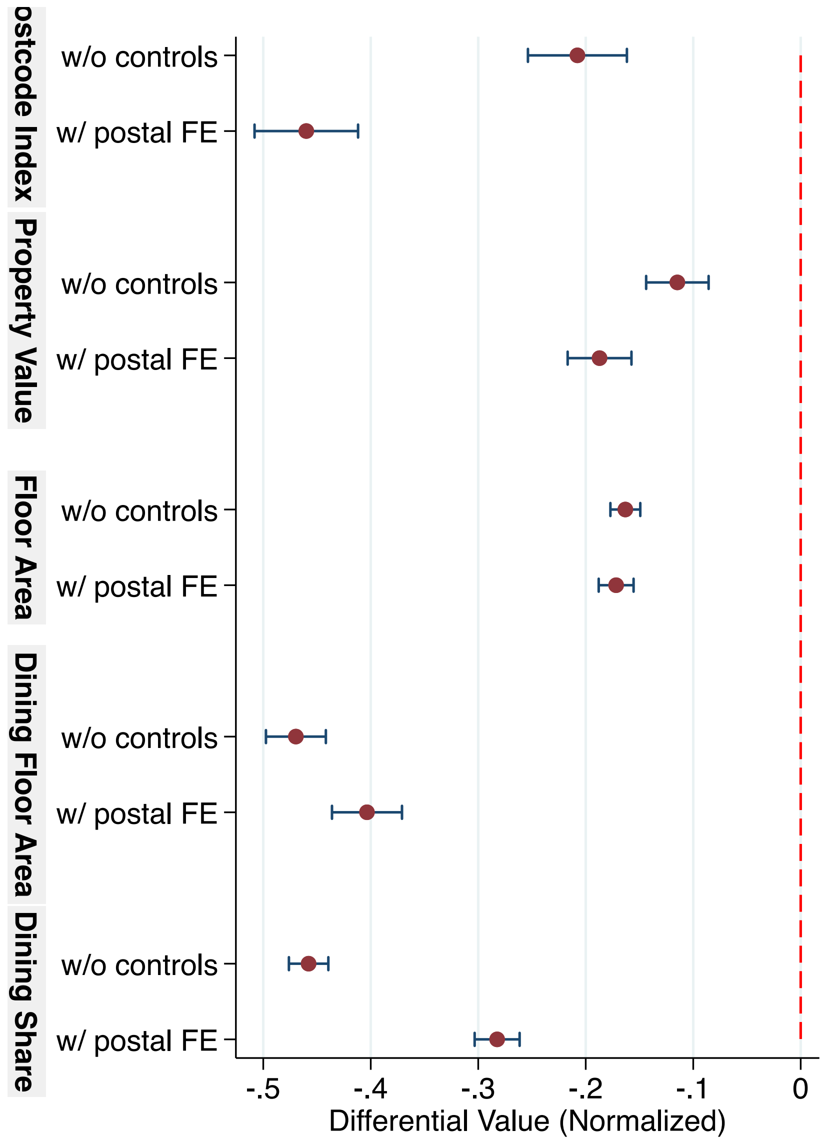
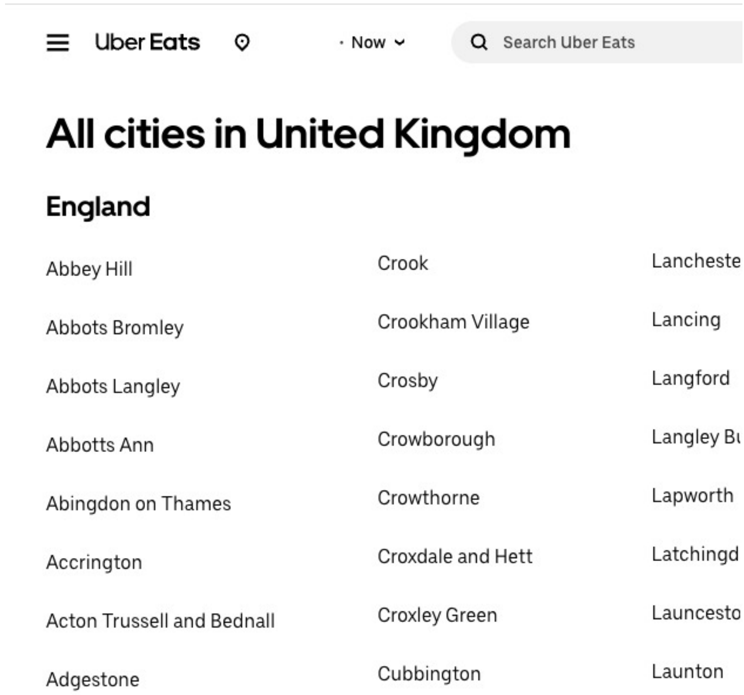
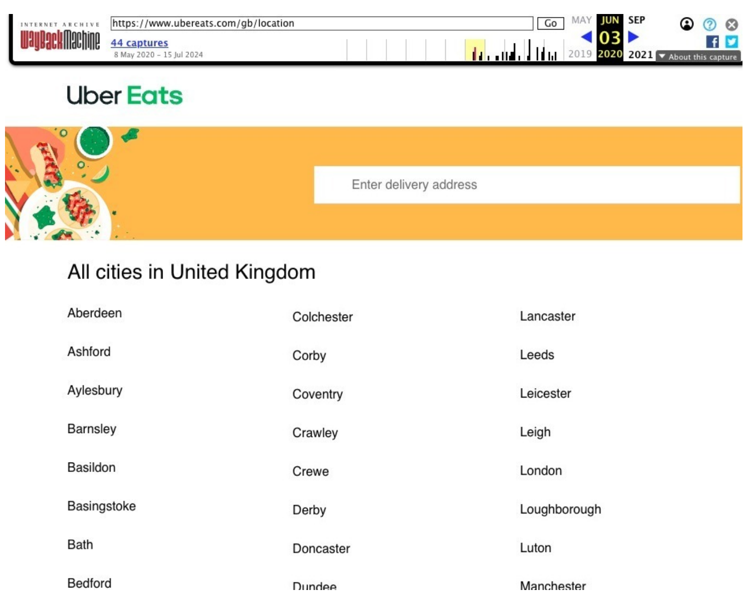


Figure A6. *Notes:* This graph presents the differences in property characteristics between restaurants listed on food delivery applications (Food App) and those not listed, among non-chain restaurants. The outcome variables include Price Index (estimated average property price within the restaurant's postcode), Property Value (total market value of the property), Total Area (overall floor area), Dining Area (floor area dedicated to dining), and Dining Share (percentage of the property's area used for dining). Each outcome is regressed on the Food App indicator both without controls and with postal district fixed effects, with estimates normalized using the dependent variable's mean. The price index is derived from Price Paid data to measure postcode-level land price, while other outcomes are sourced from the Valuation Office Agency (VOA) 2023 dataset.

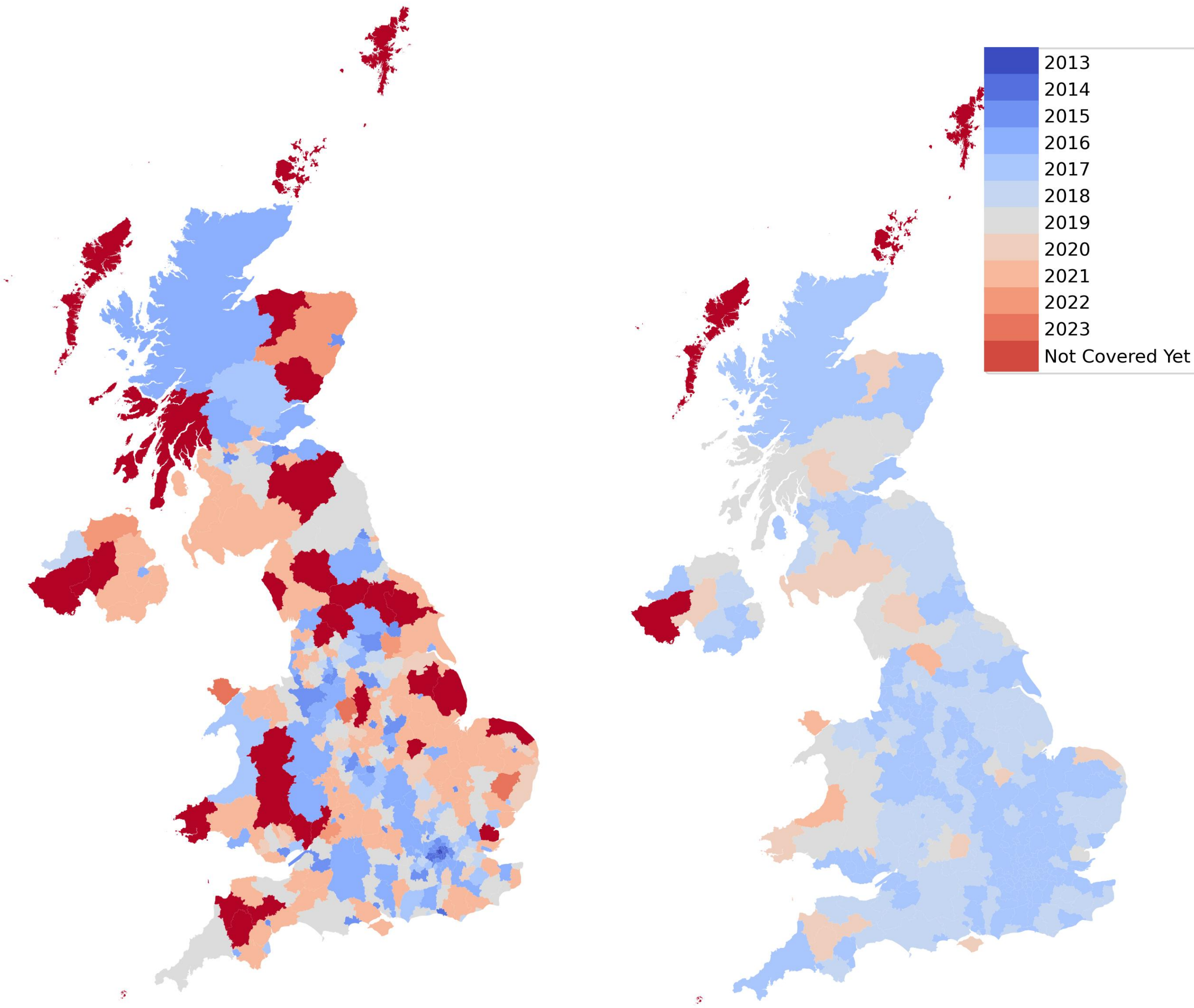


(a) UberEats Coverage Page



(b) Internet Archive

Figure A7. *Notes:* Panel (a) displays a webpage from UberEats showcasing their UK coverage area. Panel (b) illustrates the archived version of this page, retrieved from the Wayback Machine (Internet Archive) on June 3, 2020.



(a) Deliveroo Rollout

(b) UberEats Rollout

Figure A8. *Notes:* This map displays UK local authorities that have a minimum of one restaurant featured on Google Maps. Panel (a) depicts the introduction of the Deliveroo application, and Panel (b) indicates the introduction of the UberEats application. The UK local authority boundary file is sourced from here. A small number of postal districts could not be directly mapped due to updates in postal district definitions. These unmatched districts were associated with the closest matching district from the boundary file.

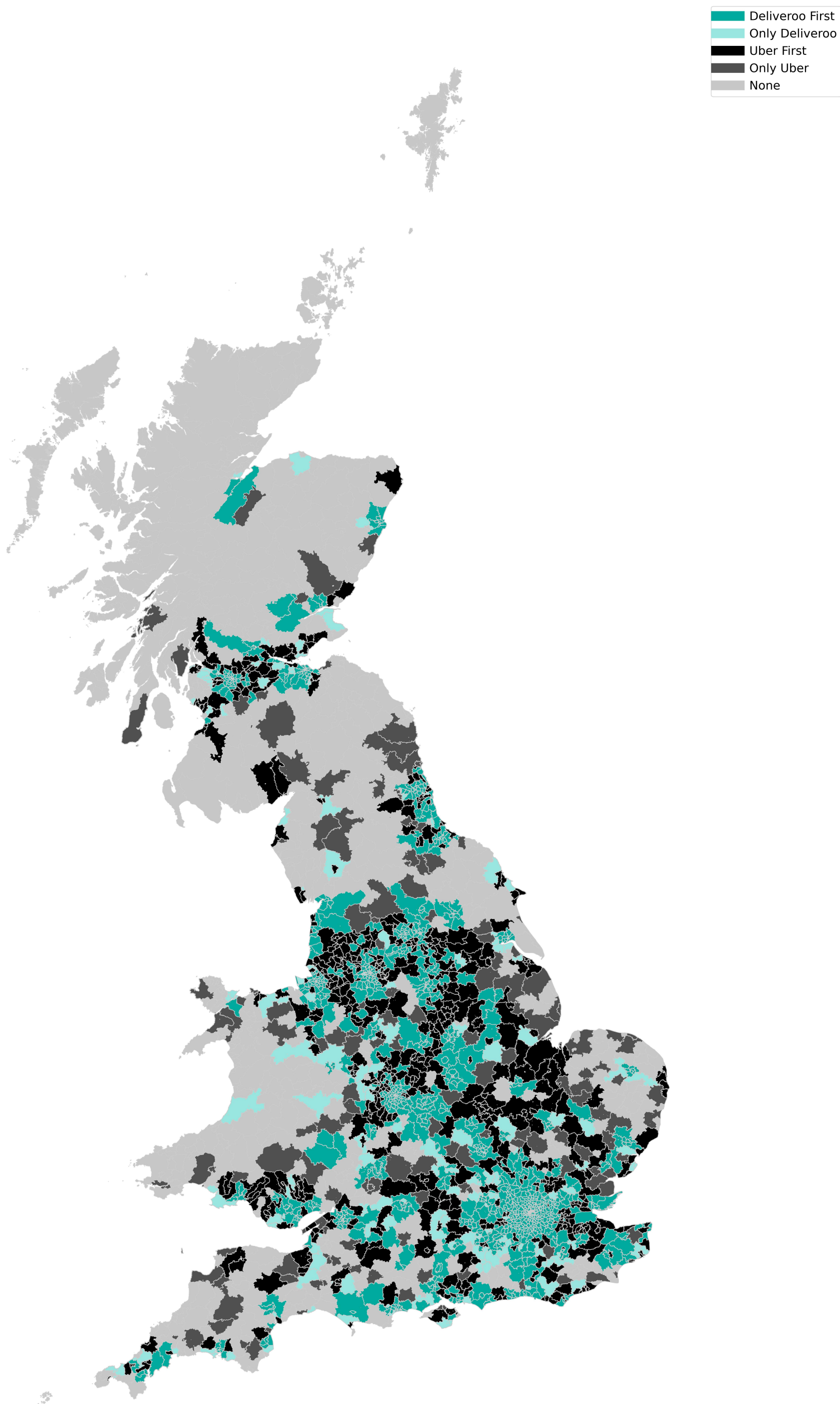
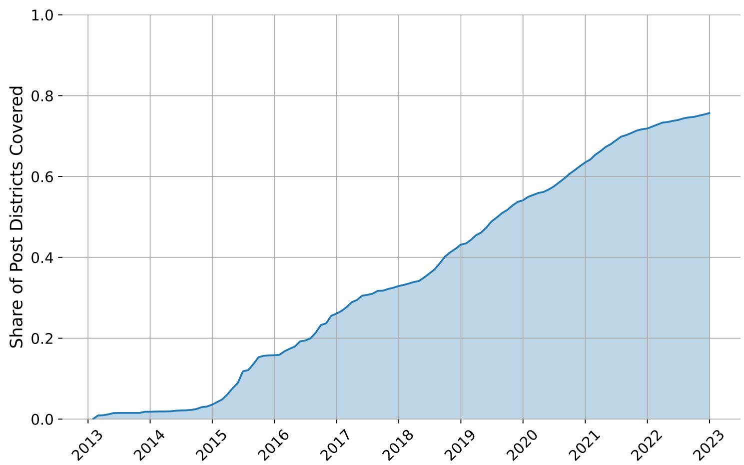
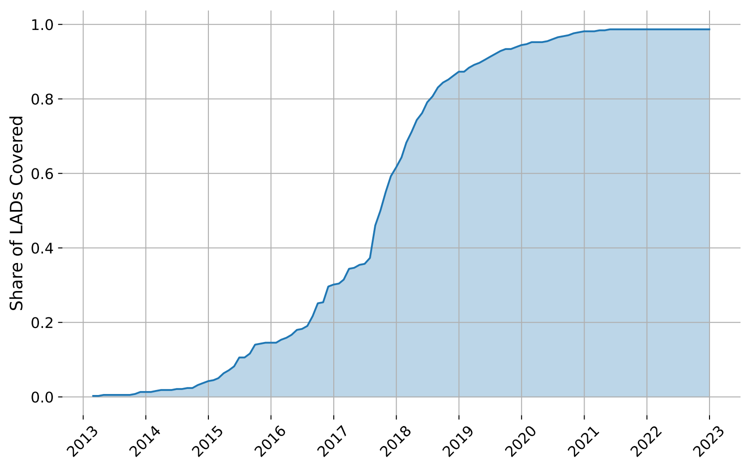


Figure A9. *Notes:* The map illustrates the rollout dynamics of Deliveroo and UberEats in UK postal districts, showing which platform entered first, which districts are only served by Deliveroo or Uber, and which districts are not served by either platform. Data is sourced from the author's scraping data collection.



(a) Share of Postal Districts Covered



(b) Share of LADs Covered

Figure A10. *Notes:* The figures illustrate the proportion of postal districts (panel a) and local authorities (panel b) covered by either UberEats or Deliveroo. The definition of penetration, i.e., rollout for each platform in each spatial unit, is discussed in section 4.

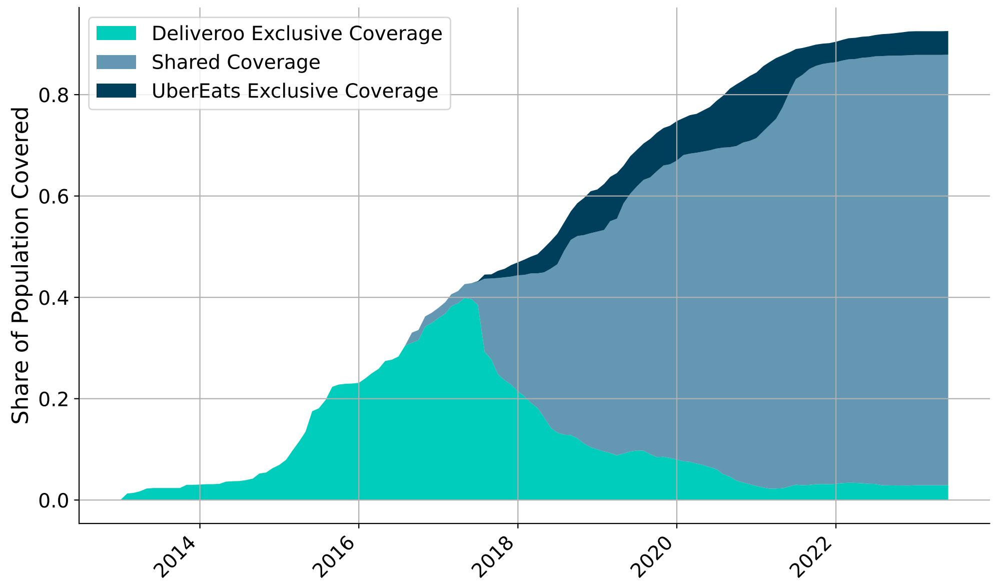


Figure A11. *Notes:* The figure illustrates the share of the population with access to Deliveroo (teal), UberEats (dark blue), and both services (light blue) over time. 'Having access' is defined for each postal district as detailed in the accompanying text, with population figures derived from the 2021 census.

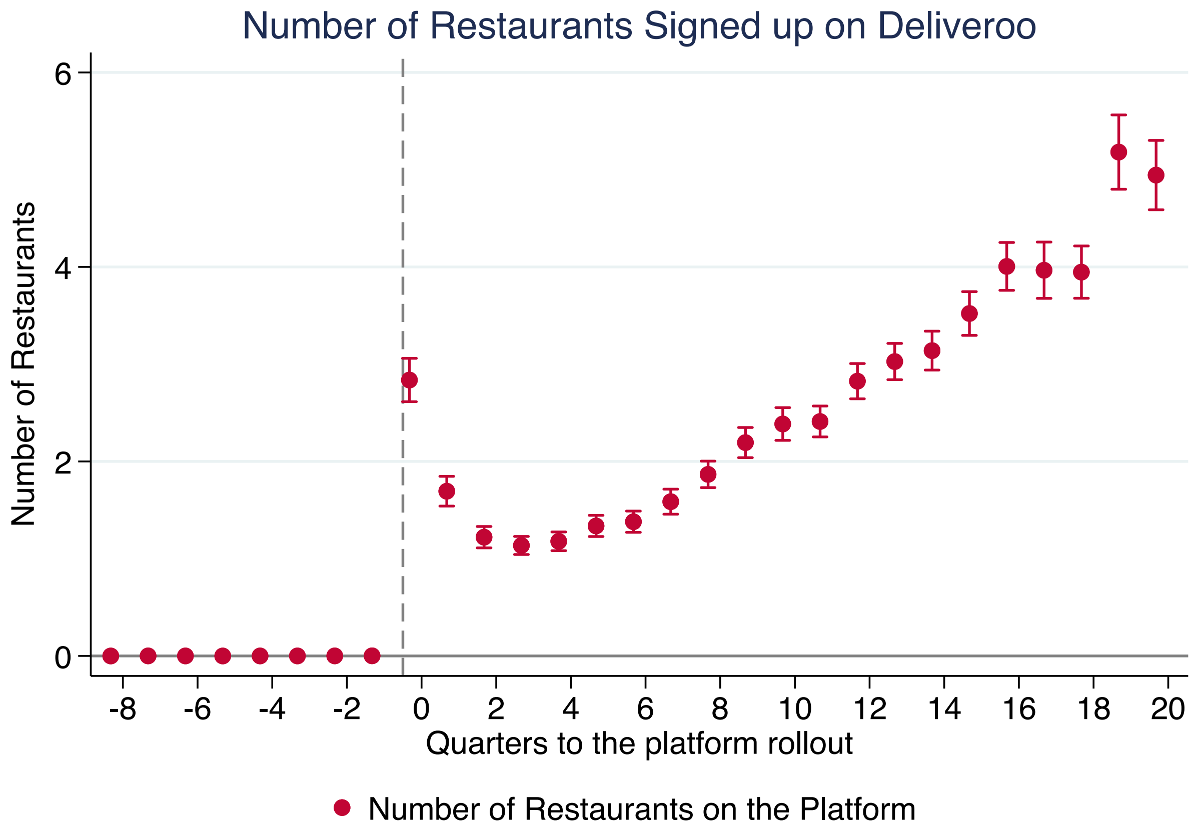
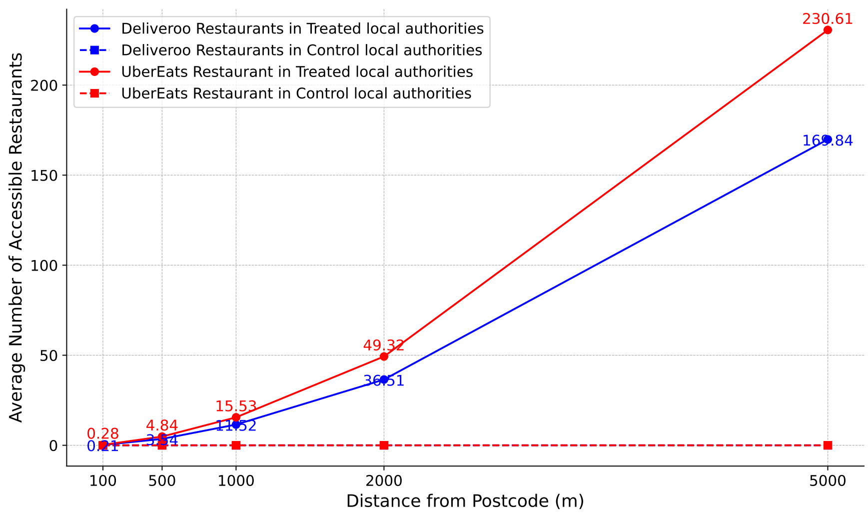


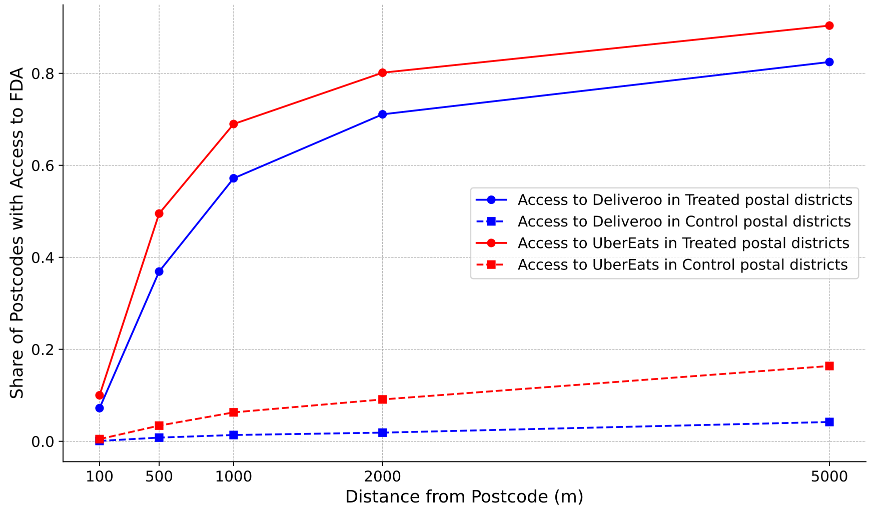
Figure A12. *Notes:* This figure presents the event study results for Deliveroo, where the outcome variable is the number of new restaurants on the platform. Borusyak *et al.* (2023) estimator is used. Postcodes with Deliveroo rollout before 2017-03 (768 postcodes) are dropped since imputation is impossible for these units as they are treated in all periods in the sample. The graph represents a fully dynamic regression incorporating all leads and lags, though only the first 12 leads and 48 lags are visually depicted.

(a) Postal District

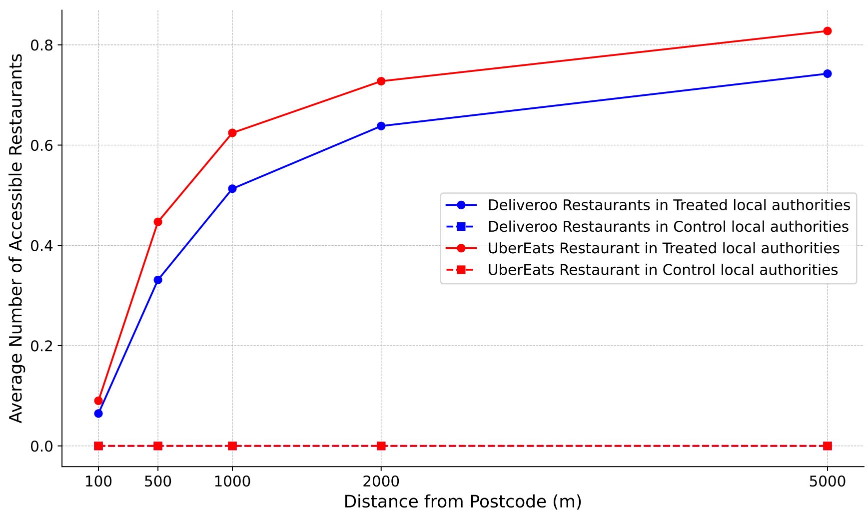


(b) Local Authority

Figure A13. *Notes:* The figure illustrates the average number of accessible restaurants on each platform as a function of distance from postcodes, comparing postcodes in treated and control spatial units as of 2023. Panel (a) shows postcodes in treated and control postal districts, while Panel (b) shows postcodes in treated and control local authorities. The definition of how units are classified into these control and treated groups is detailed in Section 4. The dataset includes 1.6 million postcodes, and the geodesic distance between a given postcode's coordinates and those of nearby restaurants is calculated. Data for this analysis were derived from the National Statistics Postcode Lookup (NSPL) and the author's calculation of Deliveroo restaurant entries.

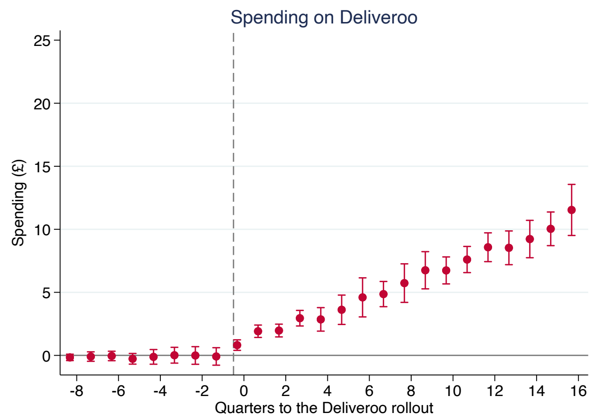


(a) Postal District

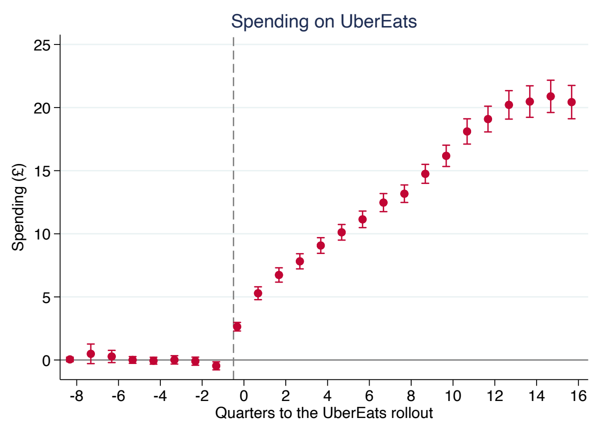


(b) Local Authority

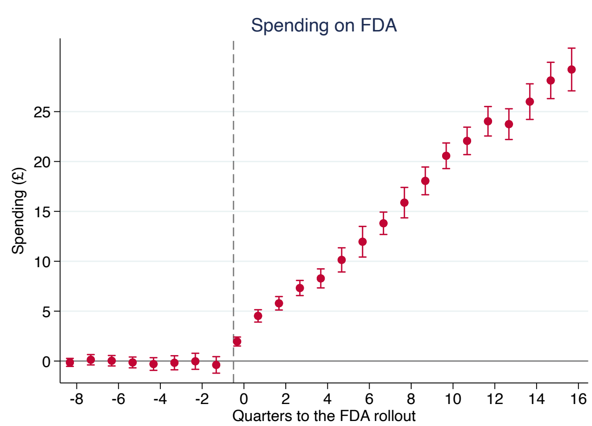
Figure A14. *Notes:* The figure illustrates the share of postcodes having access to Food App as a function of distance from postcodes, comparing postcodes in treated and control spatial units as of 2023. Panel (a) shows postcodes in treated and control postal districts, while panel (b) shows postcodes in treated and control local authorities. The definition of how units are classified into these control and treated groups is detailed in Section 4. The dataset includes 1.6 million postcodes, and the geodesic distance between a given postcode's coordinates and those of nearby restaurants is calculated. Data for this analysis were derived from the National Statistics Postcode Lookup (NSPL) and the author's calculation of Deliveroo restaurant entries.



(a) Deliveroo Rollout Analysis

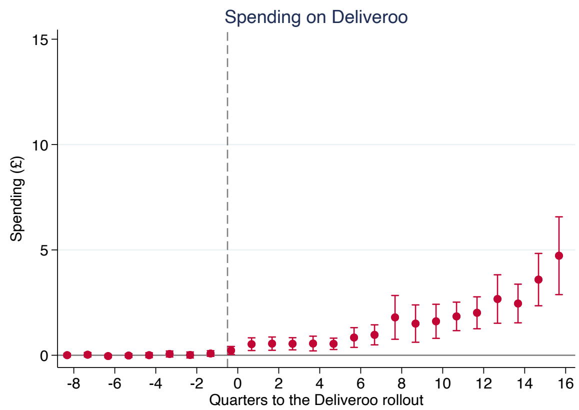


(b) UberEats Rollout Analysis

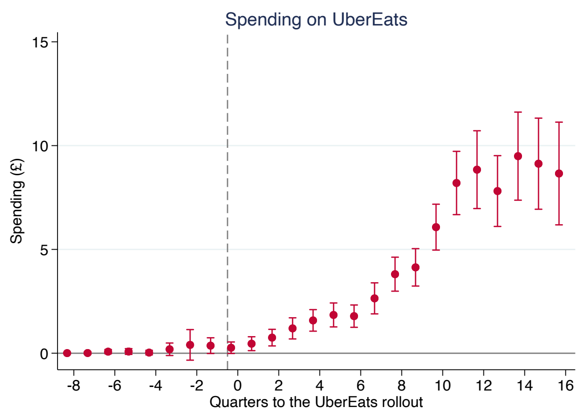


(c) Combined Platform Rollout Analysis

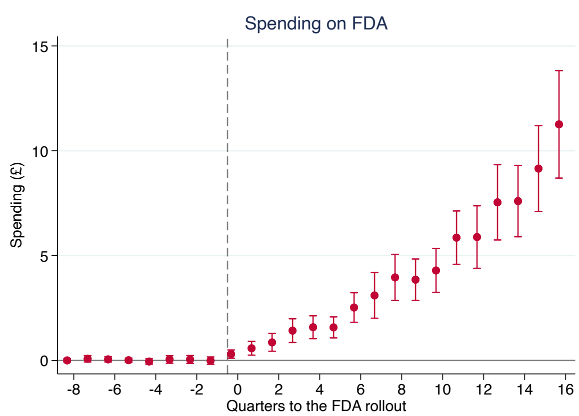
Figure A15. *Notes:* Panel (a) presents the event study results for the individual spending on Deliveroo following its rollout, panel (b) details the results for UberEats, and panel (c) shows the combined spending for Deliveroo and UberEats, based on the earliest rollout date of either platform. The outcome variable analyzed is expenditure, measured using the Fable dataset.



(a) Deliveroo Rollout Analysis



(b) UberEats Rollout Analysis



(c) Combined Platform Rollout Analysis

Figure A16. *Notes:* Panel (a) presents the event study results for the individual spending on Deliveroo following its rollout, panel (b) details the results for UberEats, and panel (c) shows the combined spending for Deliveroo and UberEats, based on the earliest rollout date of either platform. The outcome variable analyzed is expenditure, measured using Kantar's Worldpanel Take Home Purchase Panel for years 2017 to 2023.

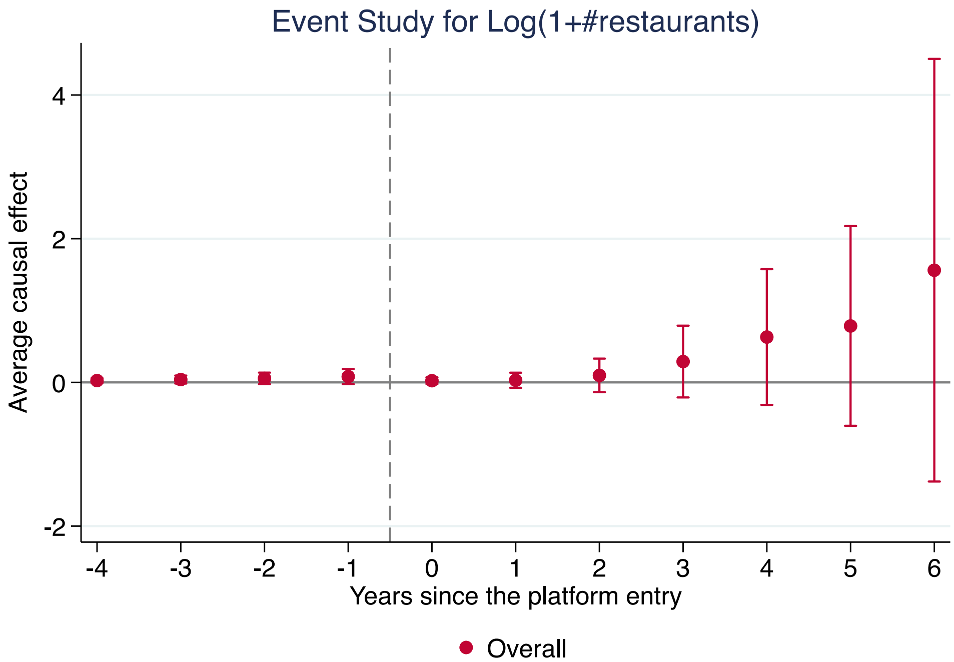
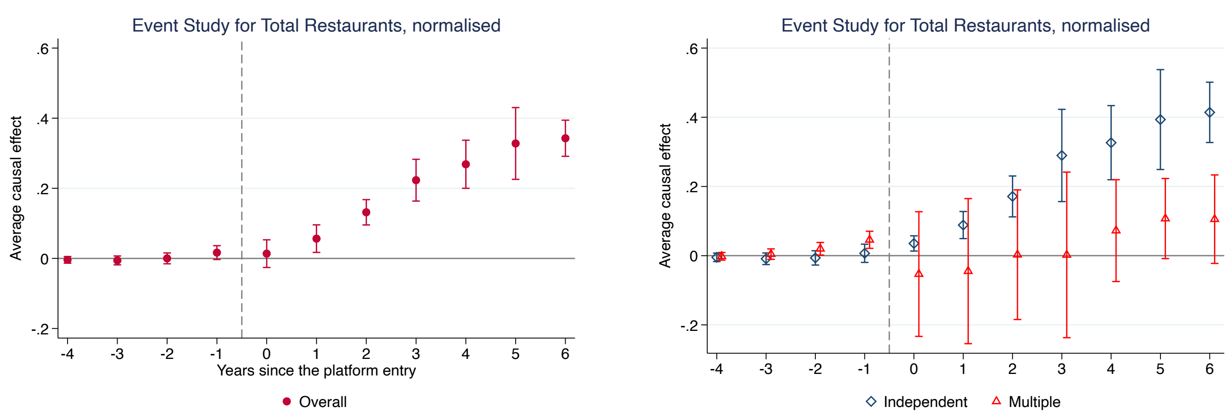


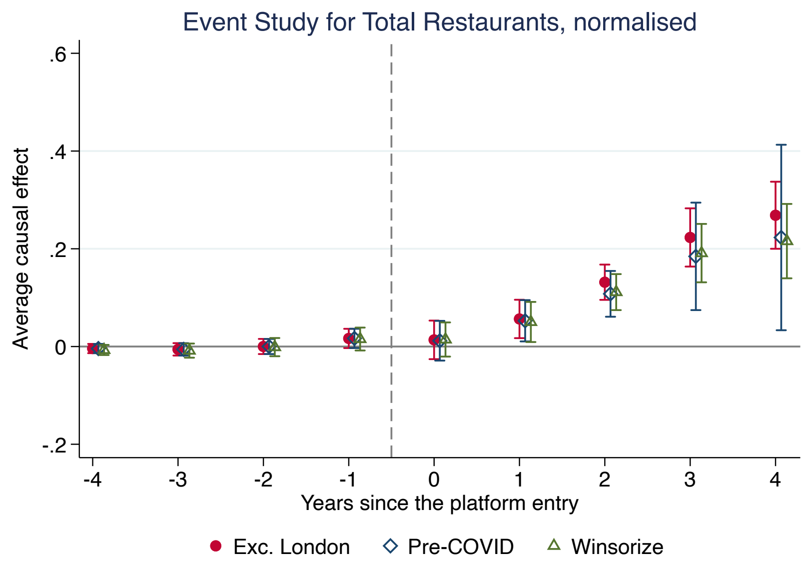
Figure A17. *Notes:* The figure shows the impact of food delivery applications on the log transformation of the number of restaurants for different cuisine types, indicating changes in the number of establishments across various culinary categories. Cuisine types are categorized as outlined in Table A8. Data is sourced from the Local Data Company (LDC).



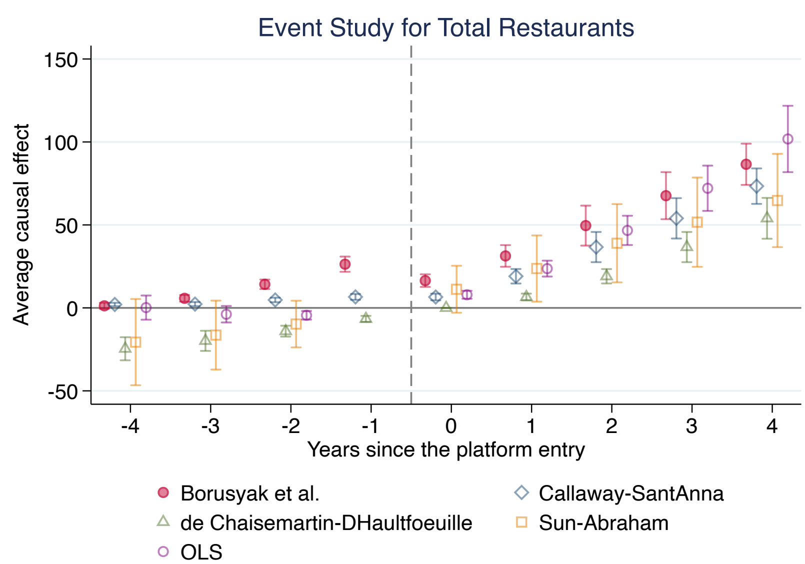
(a) Overall

(b) Independent vs Multiple

Figure A18. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on the total number of restaurants over time as a percentage of the counterfactual outcome, absent food delivery application (i.e., $P_j \equiv \hat{\beta}_j / E[\hat{y}_{st} | t = E_s + j]$ as defined in Section 5.1). Panel (b) shows the average causal effect on the number of independent versus multiple establishment restaurants normalized in the same way. The x-axis represents the years since the platform rollout, and the y-axis shows the average causal effect. Data is sourced from the Local Data Company (LDC).



(a) Robustness Checks



(b) Different Estimators

Figure A19. *Notes:* The top panel displays robustness checks where we first exclude local authorities associated with London, then remove the COVID-19 years, and finally winsorize the data at the 5th and 95th percentiles. The bottom panel presents the main analysis using different Difference-in-Differences estimators. Specifically, the Sun and Abraham (2021) estimator is calculated using last-treated units as the control group, while the Callaway and Sant'Anna (2021) estimator uses not-yet-treated units as the control group. The data is sourced from the Local Data Company, and the outcome variable is the number of restaurants in each local authority.

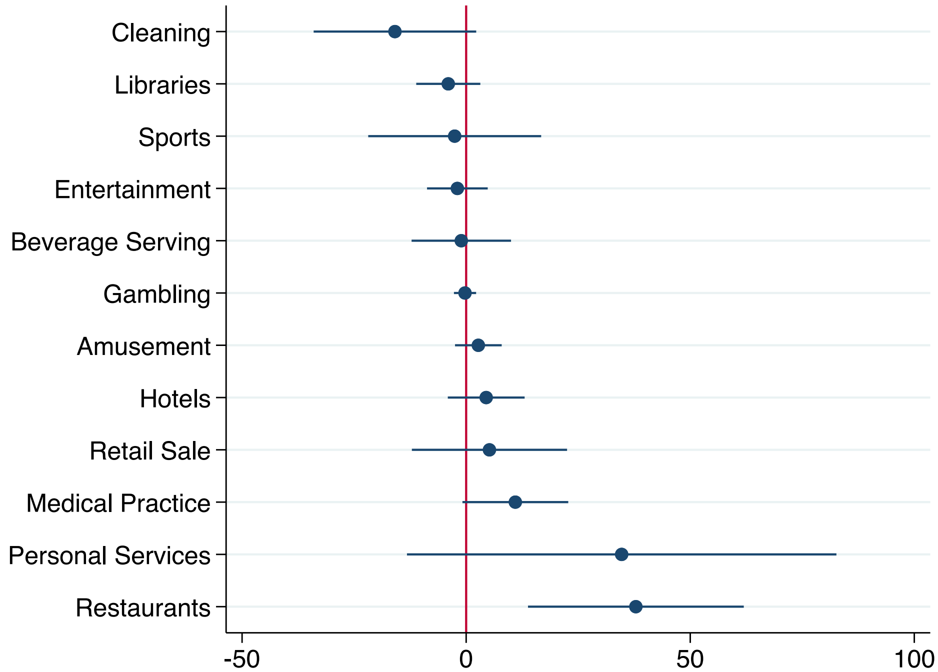


Figure A20. *Notes:* This figure displays the estimated effect of food delivery application (FDP) rollout on the number of businesses in various placebo industries. Each coefficient represents the result of a separate regression, where the outcome variable is the number of businesses in a local authority, controlling for local authority and year-fixed effects, along with local economic indicators and population interacted by time. Data are sourced from the UK Business Counts from Nomis, which is an extract from the Inter-Departmental Business Register (IDBR), for the years 2010-2023.

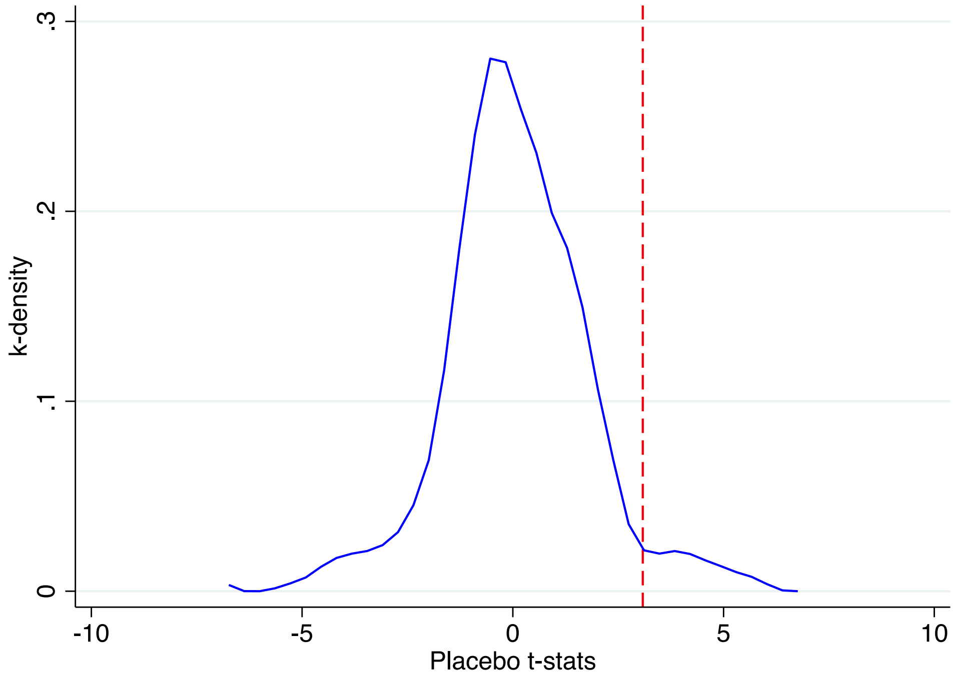


Figure A21. *Notes:* This figure presents the kernel density function of t-statistics for the effect of food delivery application (FDP) rollout on the number of businesses across all three-digit SIC 2007 industries. The vertical line indicates the true point estimate for the restaurant industry. Data are sourced from the UK Business Counts from Nomis, which is an extract from the Inter-Departmental Business Register (IDBR), for the years 2010-2023.

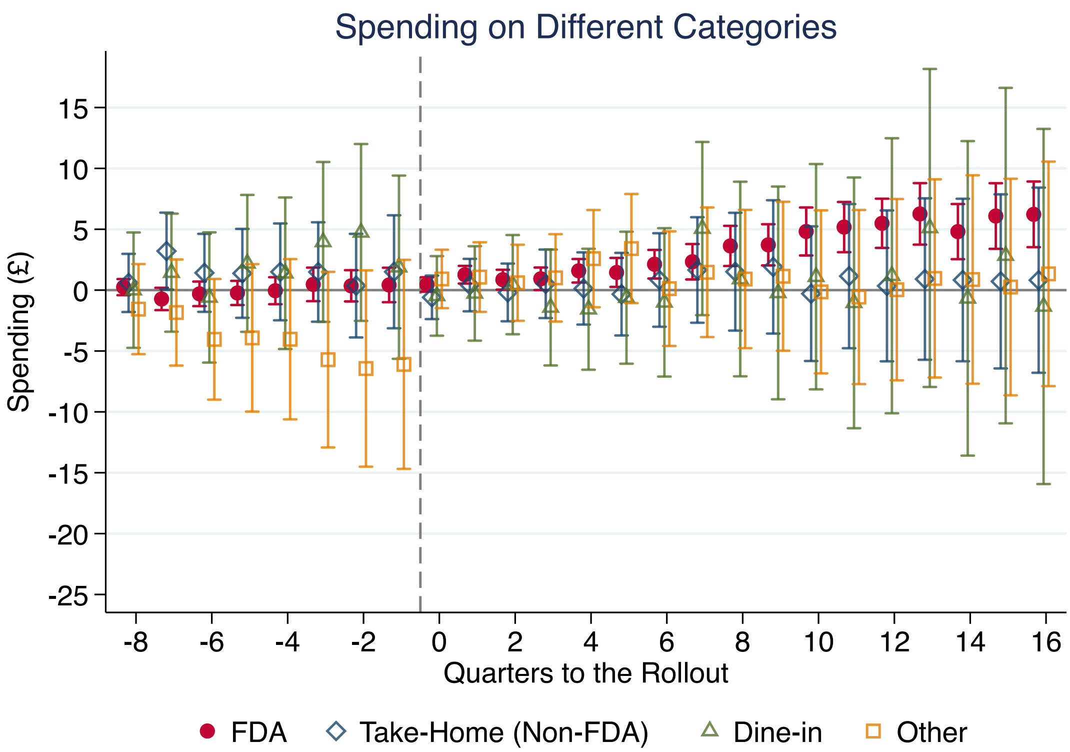
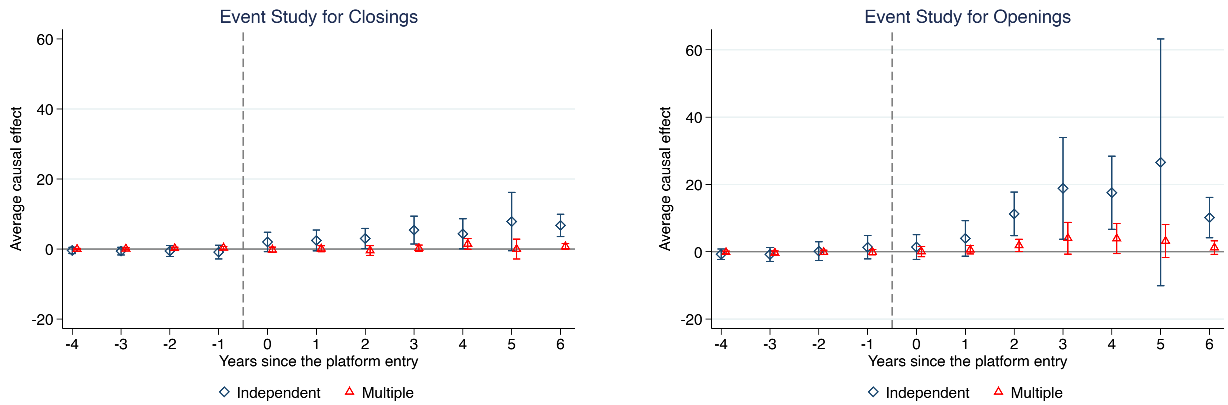
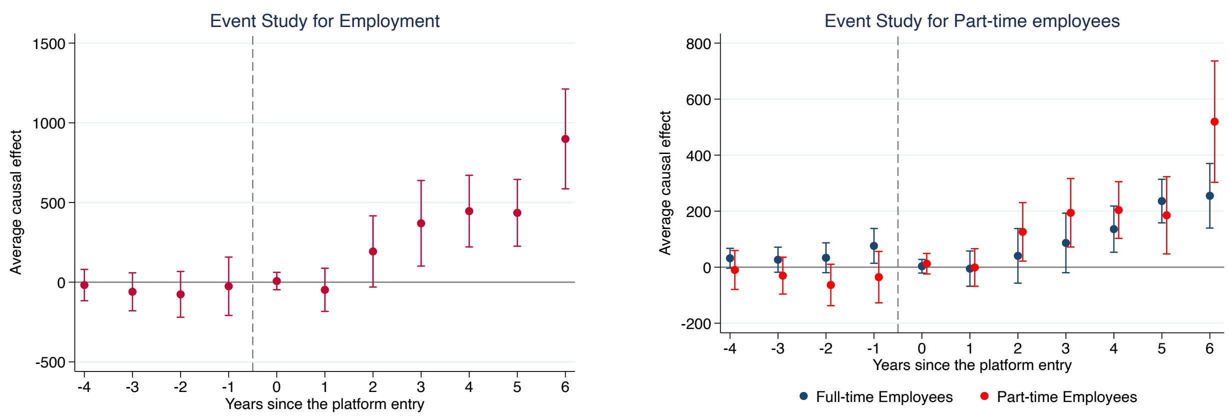


Figure A22. *Notes:* This graph shows the impact of the rollout of food delivery applications on different spending categories. Data is from Kantar's Worldpanel Out of Home Panel for the years 2017 to 2023.



(a) Closings **(b)** Openings

Figure A23. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on restaurant closings, distinguished by independent and multiple establishment types. Panel (b) shows the average causal effect on restaurant openings, also categorized by independent and multiple establishment types. The x-axis represents the years since the platform rollout, and the y-axis shows the average causal effect. Data is sourced from the Local Data Company and covers the period from 2010 to 2020.



(a) Overall Employment **(b)** Part-time vs Full-time Employment

Figure A24. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on overall employment levels in Local Authority Districts (LADs). Panel (b) shows the average causal effect on part-time versus full-time employment within the same districts. The x-axis represents the years since the platform rollout, and the y-axis shows the average causal effect. Data is sourced from the Business Register and Employment Survey (BRES) covering the period from 2015 to 2023. Full-time employees work more than 30 hours per week, while part-time employees work 30 hours or less per week. Employment includes employees plus working owners, covering self-employed workers registered for VAT or PAYE but excluding those not registered, HM Forces, and Government Supported trainees.

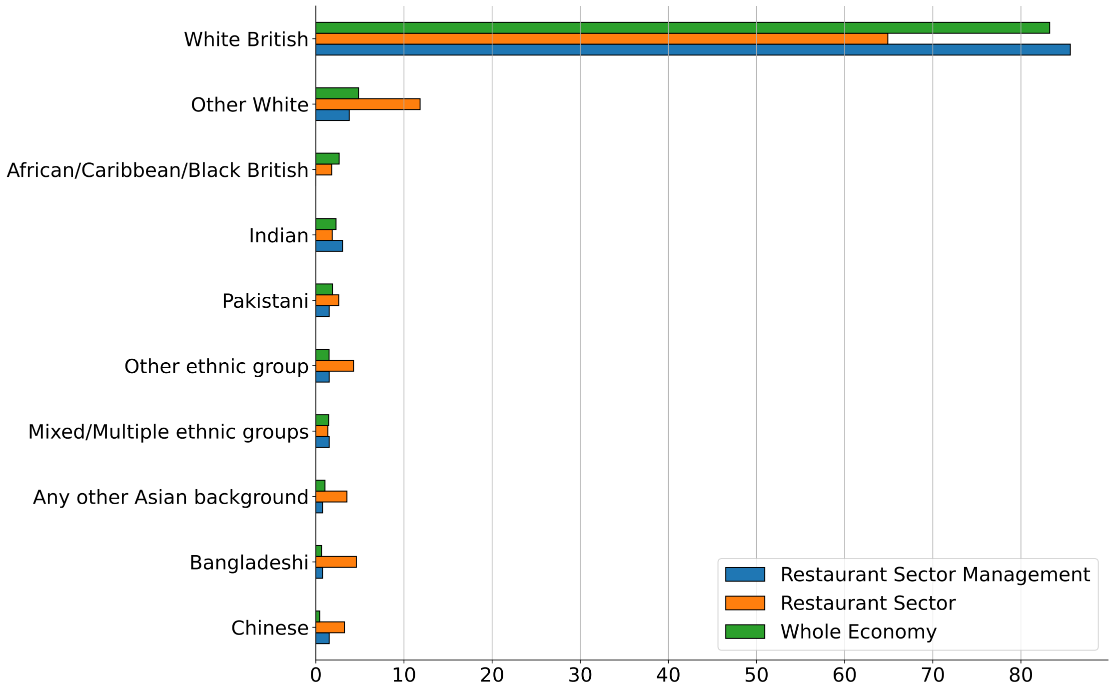
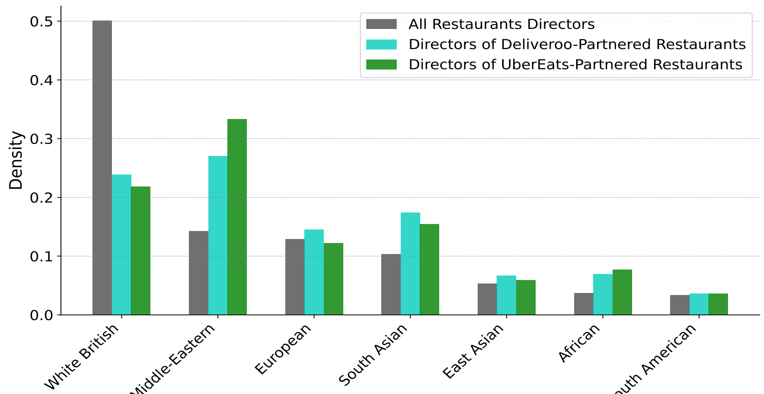
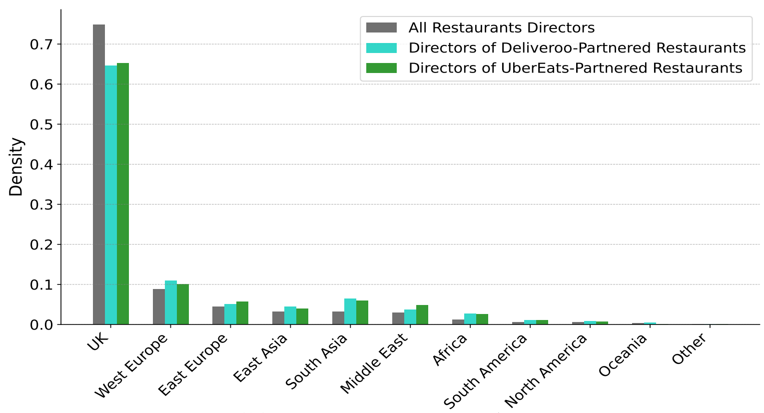


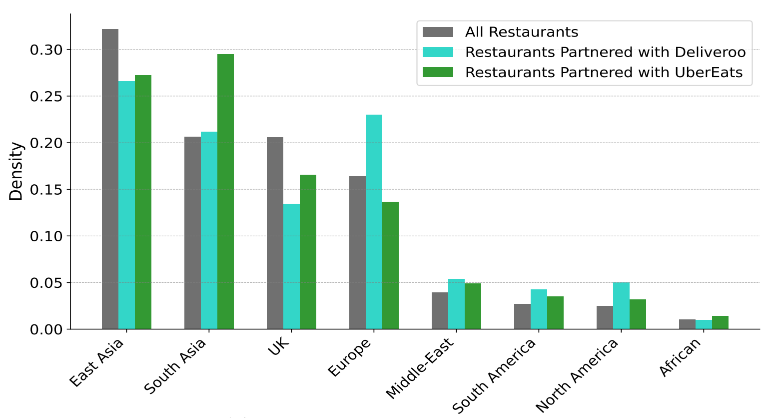
Figure A25. *Notes:* This graph shows the distribution of ethnic groups across the overall economy, the restaurant sector, and managerial positions within the restaurant sector. The data are drawn from the UK Labour Force Survey (2013Q1–2015Q4). The restaurant industry corresponds to SIC code 561, and managerial positions are based on the SOC category ”Higher managerial and professional.” ”White Irish” are grouped under ”Other White.”



(a) Directors' Ethnicity



(b) Directors' Nationality



(c) Restaurant Cuisine Type

Figure A26. *Notes:* Panel (a) shows the distribution of restaurant directors by ethnic background across three categories: all restaurant directors, Deliveroo-partnered, and UberEats-partnered restaurant directors, where directors' backgrounds are inferred from their names. Panel (b) displays the distribution by nationality across the same categories, with nationalities classified as in Table A7. Panel (c) presents the distribution of cuisine types across three categories: all restaurants in the LDC dataset, LDC restaurants matched with Deliveroo listings, and LDC restaurants matched with UberEats listings. The matching process, detailed in Section 2, utilizes fuzzy matching algorithms based on restaurant names. It focuses on geographic cuisine and excludes generic restaurants. Data for Panels (a) and (b) come from Companies House and Data for Panel (c) come from LDC.

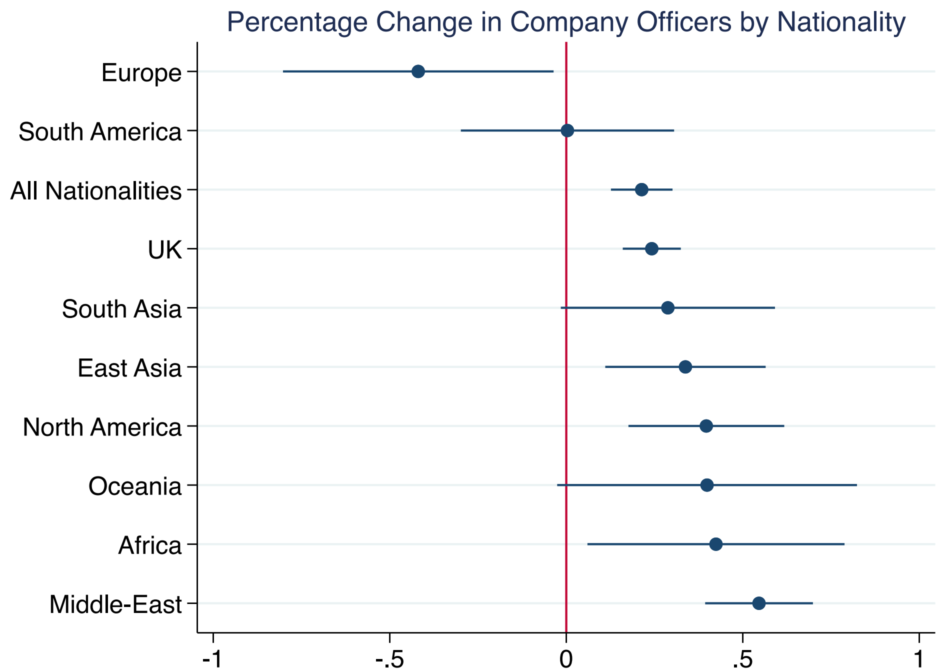
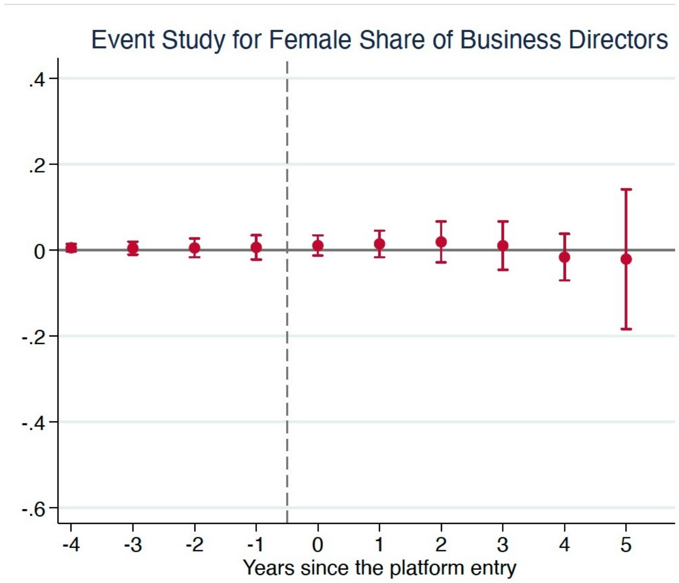
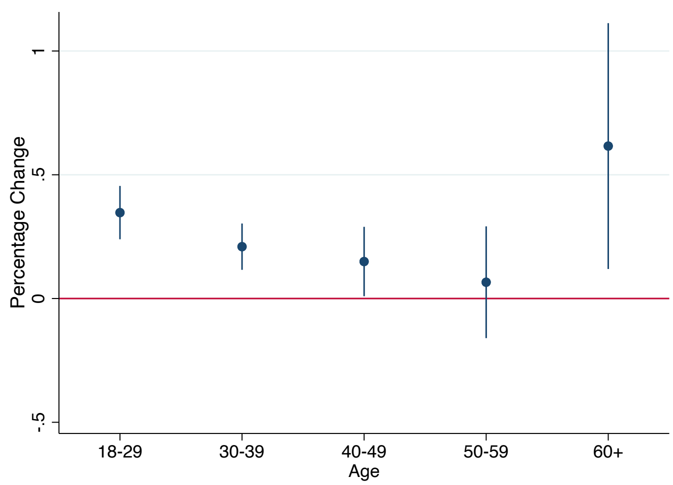


Figure A27. *Notes:* The figure shows the impact of the platform on different entrepreneur nationalities, reported as the percentage changes by computing $\Delta\hat{y}_m = \hat{\beta_m}/E(\hat{y_m}|D_{it} = 1)$, where $E(\hat{y_m}|D_{it} = 1)$ is the average predicted number of entrepreneurs from nationality m after the rollout of the platform when omitting the contribution of the treatment variable for the presence of the platform. The analysis controls for location and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from Companies House.



(a) Impact on Female Share



(b) Impact on Age

Figure A28. *Notes:* Panel (a) depicts the impact of platform entry on the share of female entrepreneurs, estimated using an event study design. Panel (b) illustrates the impact on different age groups as a percentage change, where each coefficient represents the average effect of all lags in the event study for comparability. Data is sourced from Companies House.

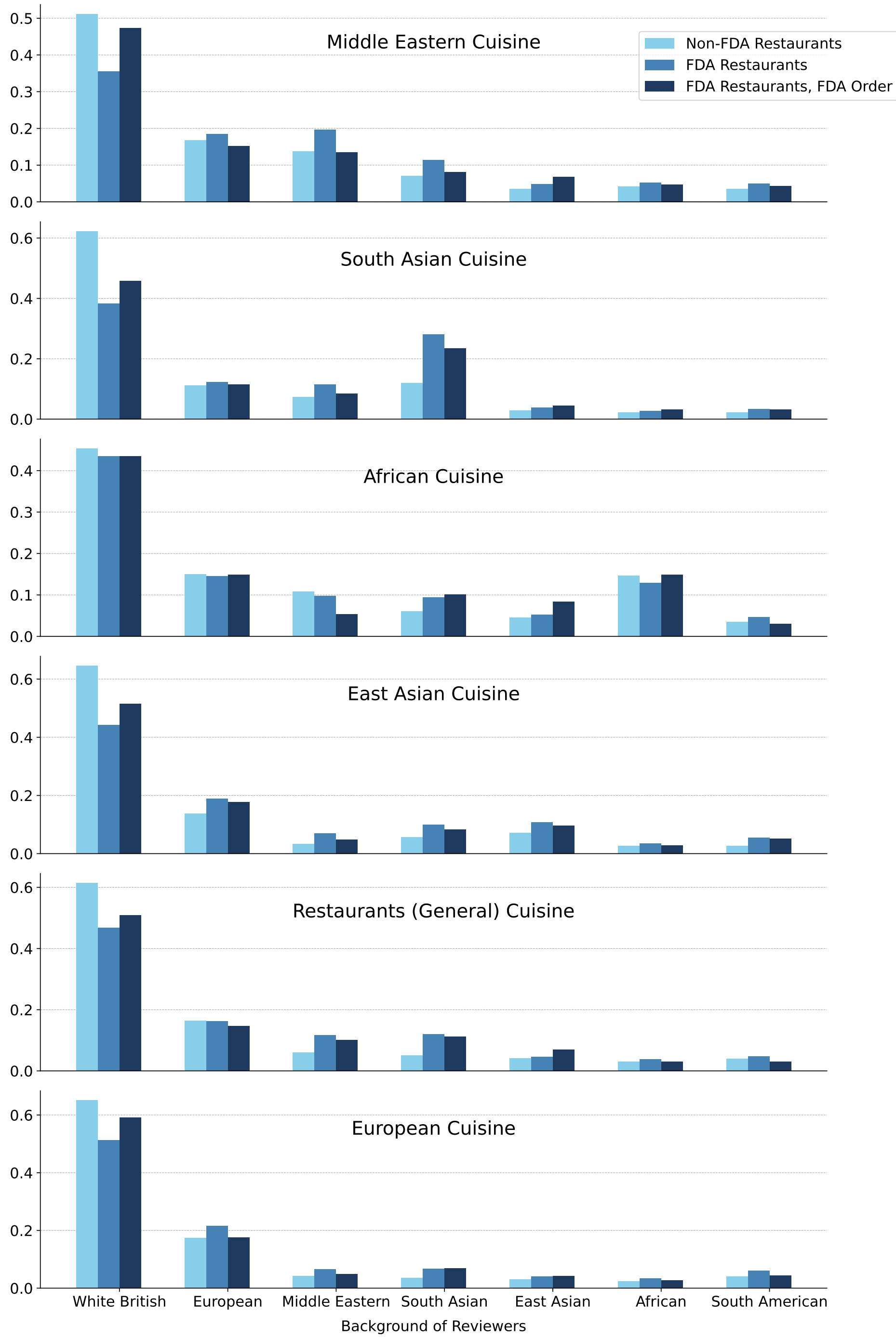


Figure A29. *Notes:* The figure illustrates the distribution of ethnicities of reviewers for different cuisines across three categories: non-partnered restaurants, app-partnered restaurants, and a subset of app-partnered restaurant customers confirmed to have placed orders through Food Apps. The data is based on restaurants on Google Maps. Cuisine types are categorized as outlined in Table A8. Ethnicities were inferred using a predictive algorithm based on first and last names.

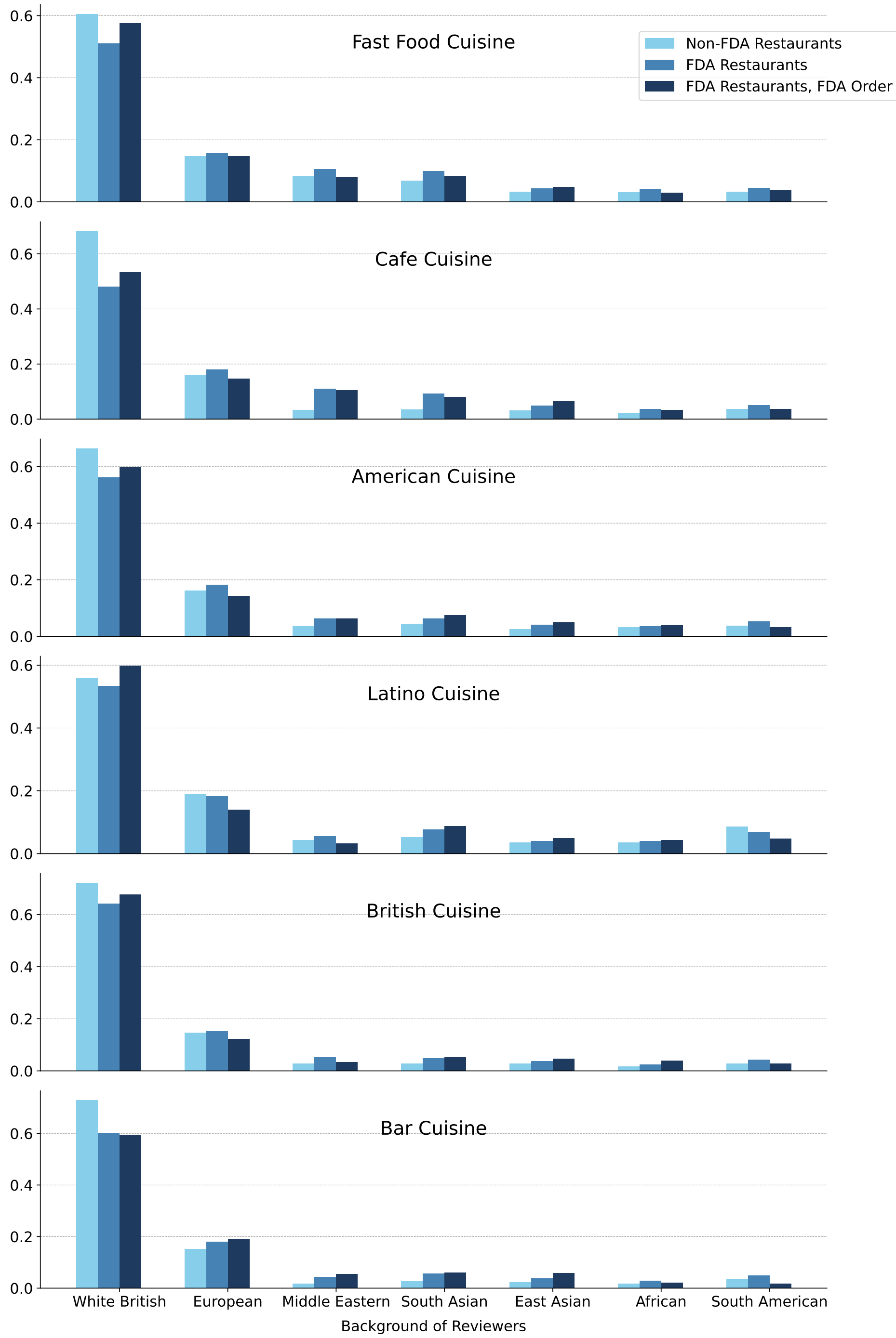


Figure A30. *Notes:* The figure illustrates the continuation of Figure A29, which shows the distribution of ethnicities of reviewers for additional cuisines. The data is sourced from app-partnered restaurants.

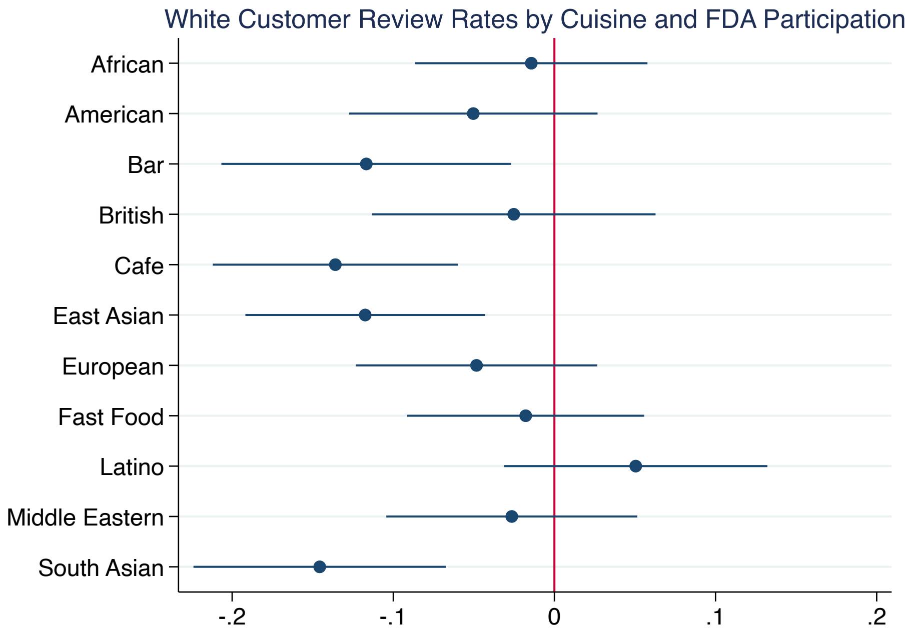
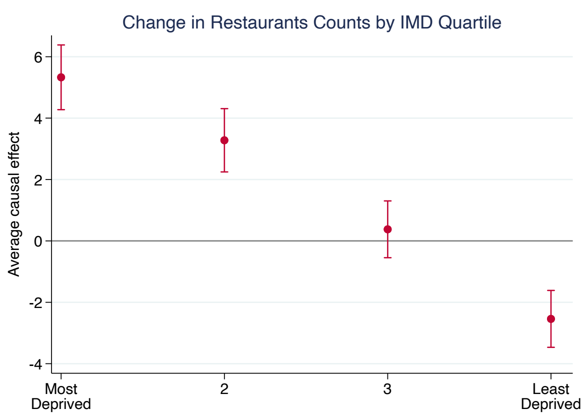


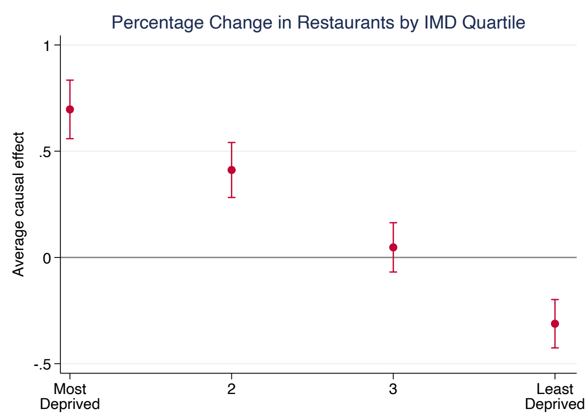
Figure A31. *Notes:* The figure illustrates the continuation of Figure A29, which shows the distribution of ethnicities of reviewers for additional cuisines. The data is sourced from app-partnered restaurants.

(a) Total Restaurants

(b) Total Restaurant, normalized



(c) Total Restaurants

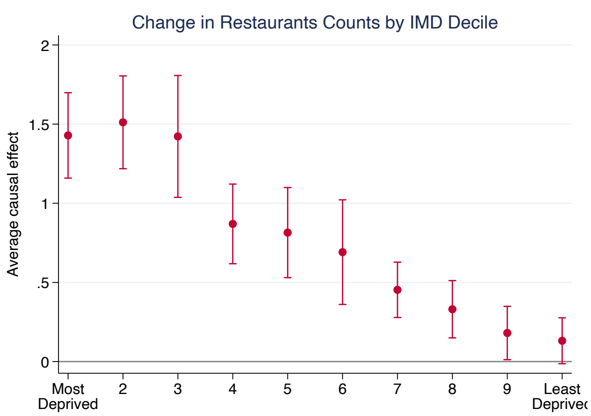


(d) Total Restaurant, normalized

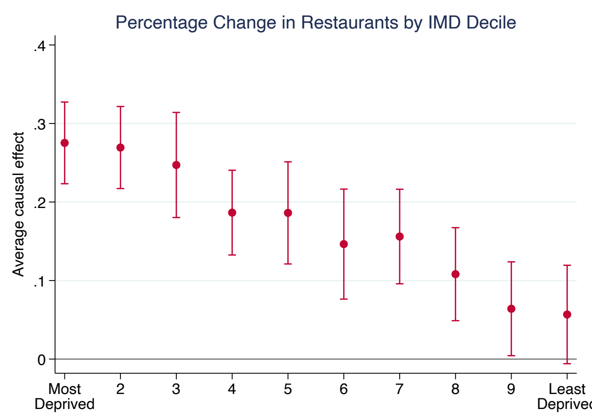
Figure A32. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on the count of the total number of restaurants, segmented by price quartile within the postal district. Panel (b) presents the average causal effect of food delivery application rollout on the total number of restaurants segmented by price quartile within postal district as a percentage of the counterfactual outcome, absent food delivery application (i.e., $P_j \equiv \hat{\beta}_j / \mathbb{E}[\hat{y}_{st} | s \in \text{ decile } j \text{ of IMD}]$ as defined in Section 5.1). Panels (c) and (d) show the same thing for IMD deciles. The analysis controls for postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

(a) Postal District Price Decile

(b) Postal District Price Decile, normalized



(c) Postal District IMD



(d) Postal District IMD, normalized

Figure A33. *Notes:* Panel (a) presents the average causal effect of food delivery application rollout on the count of the total number of restaurants, segmented by postal district physical space rice deciles. Panel (b) shows in percentage terms of the counterfactual outcome, absent food delivery application (i.e., $P_j \equiv \hat{\beta}_j / \mathbb{E}[\hat{y}_{st} | s \in \text{decile } j \text{ of IMD}]$ as defined in Section 5.1). Panel (c) presents the average causal effect of food delivery application rollout on the total number of restaurants segmented by postal district IMD deciles. Panel (d) shows it as a percentage change of the counterfactual outcome. The analysis controls for postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

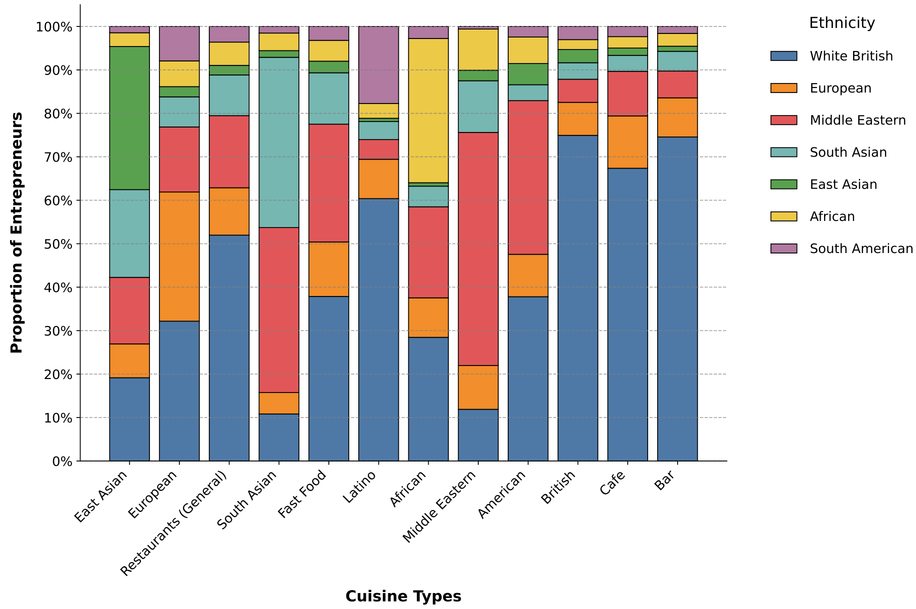


Figure A34. *Notes:* The figure displays the ethnic composition of entrepreneurs across various cuisine types. Cuisine classifications are sourced from Google Maps data, which are then matched with Companies House records containing entrepreneurs' names. As detailed in the text, ethnicity is inferred based on name analysis to estimate the representation of different ethnic backgrounds within each cuisine category..

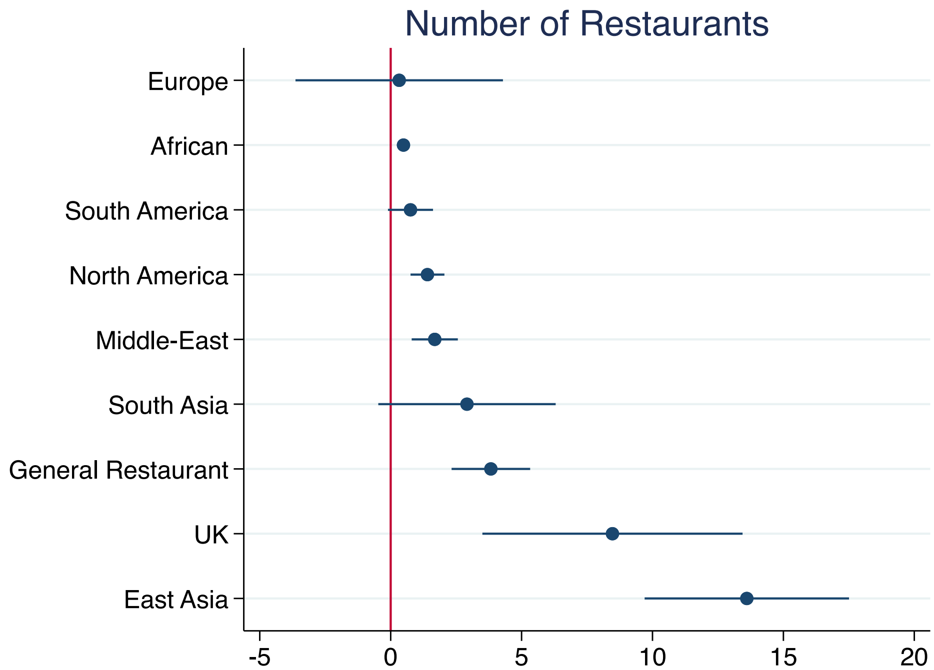


Figure A35. *Notes:* The figure shows the impact of food delivery applications on the number of restaurants for different cuisine types, indicating changes in the number of establishments across various culinary categories. Cuisine types are categorized as outlined in Table A8. Data is sourced from the Local Data Company (LDC).

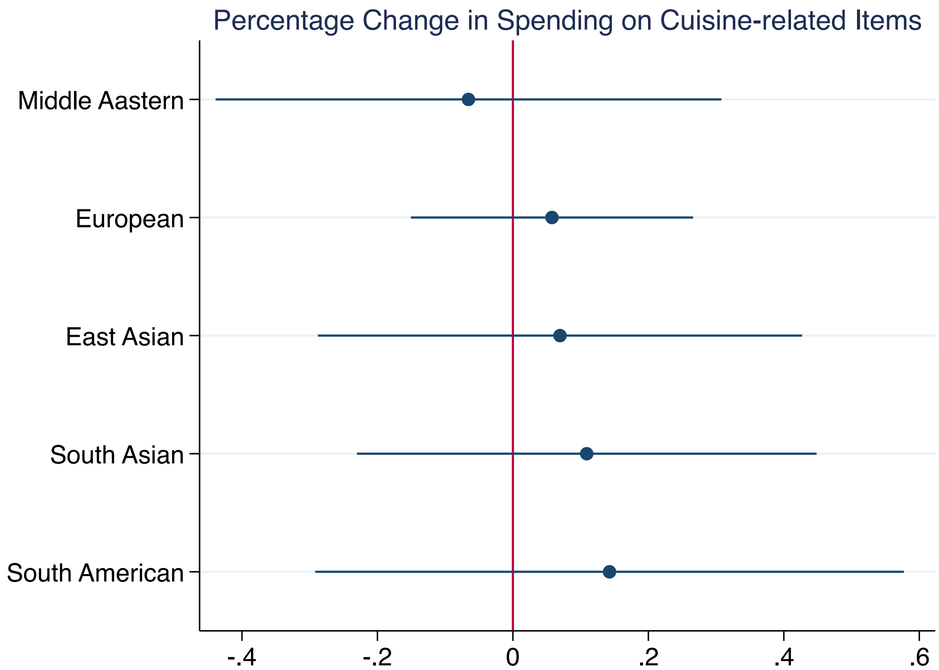


Figure A36. *Notes:* This graph displays the percentage impact of food delivery app rollouts on consumer spending from grocery stores for items representative of specific cuisines, used as placebo tests. The data, sourced from Kantar's Worldpanel Out of Home Panel, and for years 2017 to 2023, includes items like pizza, pasta, and sauerkraut for European cuisine; curry, samosa, and biryani for South Asian cuisine; burritos, nachos, and tapas for South American cuisine; falafel, hummus, and shawarma for Middle Eastern cuisine; sushi, miso, and tofu for East Asian cuisine; and cornbread, buffalo sauce, and clam chowder for North American cuisine.

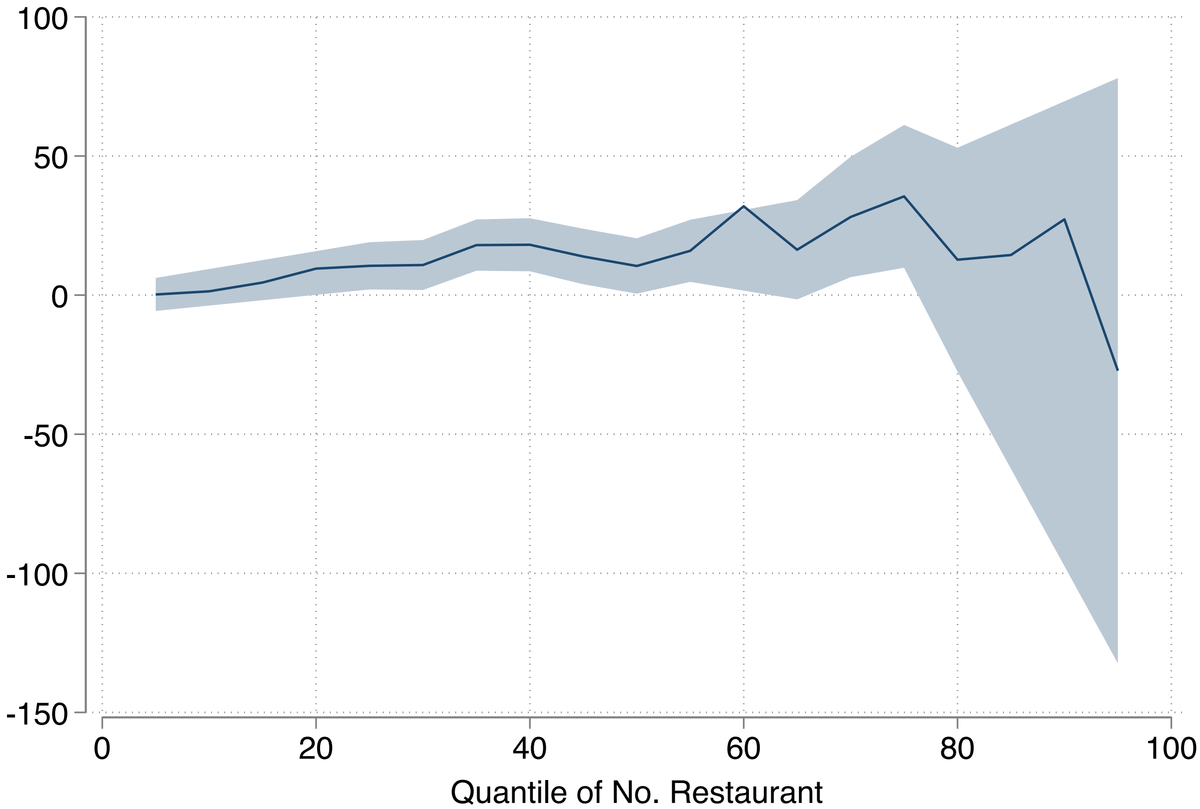


Figure A37. *Notes:* This figure graphs Quantile Treatment Effect (QTE) estimates from the RIF-DiD estimator, including a 90% confidence interval. The outcome variable is the number of restaurants in each local authority and all specifications include postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

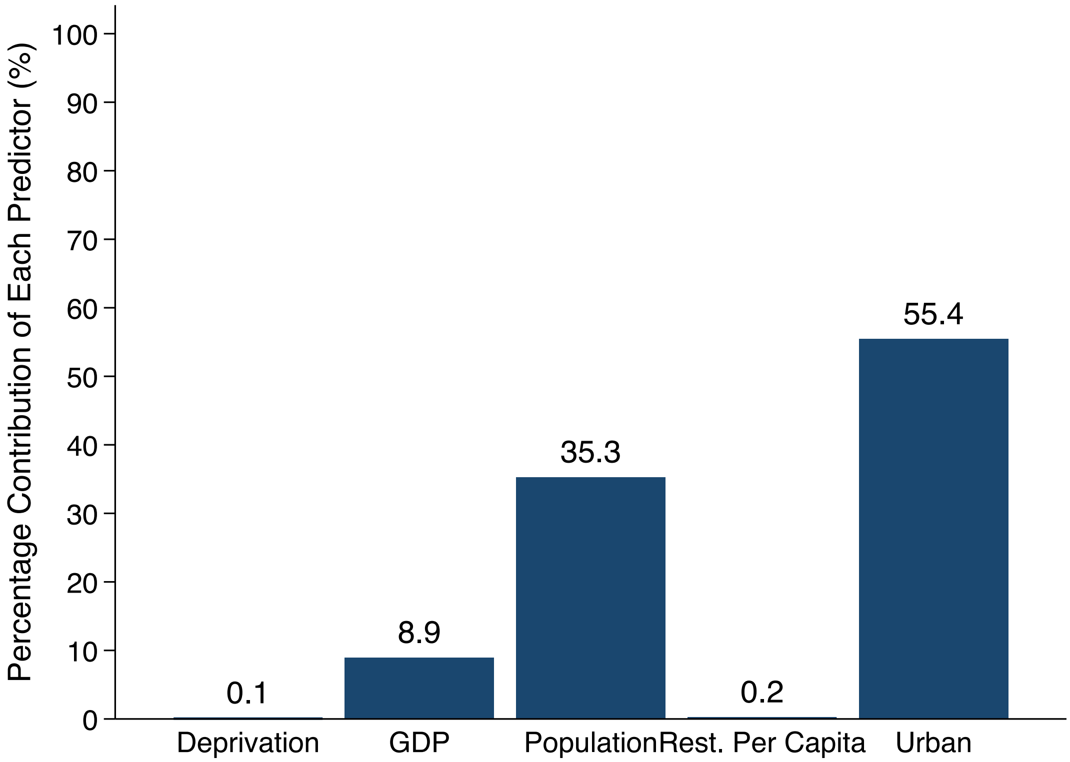


Figure A38. *Notes:* This graph shows the percentage contribution of each predictor to the R-squared value of the regression model assessing the impact of various factors on the rollout dates of food delivery applications in different postal districts. Predictors were selected using the Best Subsets Selection (BSS) method. The Shorrocks-Shapley decomposition method was used to determine the relative importance of each predictor.

Table A1. Summary of Data Sources

Variable	Fable	Kantar's Worldpanel	ONS
Income (£)			
Mean	4,380	3,236	3,083
25th Percentile	2,212	2,083	1,667
50th Percentile	3,184	2,917	2,500
75th Percentile	4,811	4,583	3,667
Age			
20-39	0.53	0.41	0.33
40-59	0.38	0.42	0.34
60+	0.09	0.17	0.33
Female Share	0.54	0.61	0.52
FDA Consumption (£)			
Mean	139.48	30.85	
Mean (conditional on using)	294.90	113.36	
50th Percentile	0.00	0.00	
75th Percentile	92.52	10.98	
90th Percentile	344.56	69.98	
Share of Restaurant Spending	0.22	0.07	
Proportion of FDA Users	0.51	0.32	

Notes: This table compares key variables across the Fable (2021-2022), Kantar (2022-2023), and ONS datasets. For Fable, income was estimated by identifying transactions likely representing income. I removed refunds and transactions under $250, based on the minimum government support threshold. Only individuals with at least 5 months of consistent income inflow were included. ONS income data is sourced from the ONS Average Household Income (UK: financial year 2020), while Kantar's Worldpanel reports income in bands, with values mapped to the midpoint of these bands. Age distribution is divided into three groups (20-39, 40-59, and 60+) for comparison across datasets. The gender share reflects the proportion of females, excluding unknown entries in Fable but included in Kantar's Worldpanel and ONS. Food App consumption data, representing household expenditure on platforms like Deliveroo, Uber Eats, and Just Eat, is shown for both Fable and Kantar's Worldpanel at the 50th, 75th, and 90th percentiles. Age and gender data for ONS are sourced from Population Estimates by the Office for National Statistics, National Records of Scotland, and the Northern Ireland Statistics and Research Agency.

Appendix A9. Tables

Table A2. Restaurants on Platform vs Non-Platform Restaurants

	Q1	Q2	Q3	Q4
Price Level	1.14	0.92	0.67	0.53
Average Reveiw	1.42	1.17	0.74	0.53
Number of Reviews	0.41	0.67	1.08	1.99
Opening Year	0.95	0.86	1.02	1.24
Number of Nearby Sales	0.37	0.60	1.07	2.13
Number of Nearby Properties	0.38	0.59	1.09	2.12
Nearby Property Price	0.38	0.57	1.11	2.11
Within-District Property Price	1.11	1.09	0.96	0.86

Notes: This table conducts a comparative analysis between restaurants listed on Deliveroo and those not affiliated with the platform. Quartiles (Q1 through Q4) are calculated based on the distributions within the complete dataset of restaurants for each measure. Each quartile in the table represents the ratio of Deliveroo to non-Deliveroo restaurants, calculated by comparing the proportion of Deliveroo restaurants within each quartile to the proportion of non-Deliveroo restaurants in the same quartile. This analysis aims to highlight potential differences in the geographical and economic landscapes between Deliveroo-participating restaurants and the wider restaurant sector.

Table A3. Summary of UK Business Counts

Employment Sizeband	Company	Private Non-Company	Non-Private
Panel A: Local Units			
Total	95,200	22,465	540
Micro (0 to 9)	64,655	19,775	400
Small (10 to 49)	27,790	2,660	130
Medium-sized (50 to 249)	2,690	30	0
Large (250+)	65	0	0
Panel B: Enterprises			
Total	79,155	22,215	380
Micro (0 to 9)	59,935	19,540	280
Small (10 to 49)	17,635	2,645	90
Medium-sized (50 to 249)	1,215	30	5
Large (250+)	365	0	0

Notes: The data is derived from 'UK Business: Activity, Size and Location', utilizing an extract from the Inter-Departmental Business Register (IDBR) on businesses with a restaurant code that were live at a reference date in March 2023. An 'enterprise' refers to the entire business, encompassing all individual sites or workplaces. It is defined as the smallest aggregation of legal units (usually based on VAT and/or PAYE records) that possesses a degree of autonomy within an enterprise group. A 'local unit' represents an individual site (e.g., a factory or shop) linked to an enterprise, also known as a workplace. In this context, 'Private Non-Company' includes Partnerships and Sole Proprietorships, while 'Non-Private' encompasses Non-Profit Bodies or Mutual Associations, Public Corporations, and entities under Central Government or Local Authority ownership.

Table A4. Summary of Data Sources

Dataset	Source	#Restaurants	Time Period	Information
Deliveroo	Scraping	50,000	2021-2024	Name, cuisine, postcode
UberEats	Scraping	63,000	2021-2024	Name, cuisine, postcode
Company House	Official (Scraped)	30,000	2010-2024	Name, age, and nationality of directors, registered address postcode
Local Data Company	Proprietary Data	80,000	2010-2024	Name, cuisine, postcode, entry and exit dates
IDBR	Official	70,000	2010-2024	Size, independent vs multiple
Google Maps	API call Scraping	180,507	2024	Name, cuisine, geolocation, average ratings, total number of reviews, names' of reviewers, price indicators

Notes: This table provides a summary of the data sources used in the analysis. The data for Deliveroo and UberEats was webscraped, while the data for Google Maps was partly scraped and partly fetched using API calls. The "No. of Restaurants" column indicates the number of restaurants included in the dataset, with the figures for UberEats and Deliveroo corresponding to the most recent batch of data. The "Time Period" column specifies the coverage period for each dataset. The "Information" column describes the types of data collected from each source.

Table A5. Official Announcements of Rollout

Region	Date	#Link
London Central	16 Jun 2016	uber.com/en-GB/newsroom/ubereats-9
London Zone 2	29 Sep 2016	uber.com/en-GB/newsroom/ubereats-zone2
Manchester	8 Feb 2017	uber.com/en-GB/newsroom/whos-hungry-manchester-introducing-ubereats
Bromley	15 Feb 2017	uber.com/en-GB/newsroom/ubereats-london-coverage-area
Birmingham	9 Mar 2017	uber.com/en-GB/newsroom/whos-hungry-birmingham-introducing-ubereats
Edinburgh	25 Apr 2017	uber.com/en-GB/newsroom/ubereats-edinburgh-is-here
Glasgow	4 May 2017	uber.com/en-GB/newsroom/serving-up-ubereats-in-glasgow
Leeds	11 May 2017	uber.com/en-GB/newsroom/leeds-whos-hungry
Nottingham	12 May 2017	uber.com/en-GB/newsroom/nottingham-whos-hungry
Liverpool	30 May 2017	uber.com/en-GB/newsroom/liverpool-whos-hungry
Southampton	30 May 2017	uber.com/en-GB/newsroom/southampton-whos-hungry
Leicester	1 Jun 2017	uber.com/en-GB/newsroom/leicester-whos-hungry
Sheffield	7 Jun 2017	uber.com/en-GB/newsroom/ubereats-launches-in-sheffield
Cardiff	7 Jun 2017	uber.com/en-GB/newsroom/ubereats-launches-in-cardiff
Swansea	7 Jul 2017	uber.com/en-GB/newsroom/ubereats-launches-in-swansea
Bristol	26 Jul 2017	uber.com/en-GB/newsroom/ubereats-launches-in-bristol
Guildford	26 Jul 2017	uber.com/en-GB/newsroom/ubereats-launches-in-guildford
Bath	26 Jul 2017	uber.com/en-GB/newsroom/ubereats-launches-in-bath
Derby	3 Aug 2017	uber.com/en-GB/newsroom/ubereats-launches-in-derby/
Chelmsford	3 Aug 2017	uber.com/en-GB/newsroom/ubereats-launches-in-chelmsford
Norwich	10 Aug 2017	uber.com/en-GB/newsroom/ubereats-launches-in-norwich
Windsor	10 Aug 2017	uber.com/en-GB/newsroom/ubereats-launches-in-windsor
Portsmouth	10 Aug 2017	uber.com/en-GB/newsroom/ubereats-launches-in-portsmouth

Notes: This table provides a summary of the UberEats rollout dates across various regions in the UK. The "Region" column lists the specific areas where UberEats was launched, and the "Date" column indicates the respective launch dates. The "Link" column contains shortened URLs to the official announcements on the Uber Newsroom website.

Table A6. Productivity of Minority-own and Platform-affiliated and Other Restaurants

	Google Average Review		
	(1)	(2)	(3)
FDA Restaurant	-0.10		-0.13
	(0.01)		(0.01)
Minority-run		-0.14	-0.16
		(0.01)	(0.01)
Minority $\times$ FDA			0.11
			(0.02)
Mean of dep. variable	4.46	4.46	4.46
Observations	8084	8084	8084

Notes: This table compares productivity levels, measured by the average Google review for different restaurants. The outcome variable is the Google Average Review, extracted from Google Maps in Q1 2024. These listings are then matched with Company House, Deliveroo, and UberEats listings. The matching process uses fuzzy algorithms based on restaurant names and postcodes, and only observations with a high likelihood of a successful match are retained. Minority-owned is a binary variable equal to one if the most common background of the restaurant's directors is inferred to be "African," "Muslim," "East Asian," or "South American." Food App equals one if the restaurant is also listed on either Deliveroo or UberEats.

Table A7. Classification of Nationalities

Group	Countries
UK	United Kingdom, England, Wales, Scotland, Northern Ireland
North America	United States, Canada
Europe	Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Guernsey, Hungary, Iceland, Ireland, Italy, Jersey, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Sweden, Switzerland, Ireland, Albania, Armenia, Azerbaijan, Belarus, Bosnia, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Kosovo, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Ukraine
Middle East	Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Palestine, Qatar, Saudi Arabia, Syria, United Arab Emirates, Yemen, Turkey, Afghanistan, Armenia, Bahrain,
South Asia	Bangladesh, Bhutan, India, Nepal, Pakistan, Sri Lanka
East Asia	Brunei, Burma, Cambodia, China, Indonesia, Japan, Kazakhstan, Korea, Laos, Macau, Malaysia, Maldives, Mongolia, Myanmar, North Korea, Philippines, Singapore, South Korea, Taiwan, Thailand, Turkmenistan, Uzbekistan, Vietnam, Kyrgyzstan, East Timor
Africa	Algeria, Angola, Botswana, Burkina Faso, Burundi, Cameroon, Congo, Djibouti, Egypt, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea-Bissau, Guinea, Ivory Coast, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe
Oceania	Australia, Vanuatu, Fiji, Nauru, New Zealand, Papua New Guinea, Samoa, Tonga
South America	Antigua, Argentina, Bahamas, Barbados, Belize, Bermuda, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Trinidad and Tobago, Uruguay, Venezuela, Panama
Other	Stateless, Stateless Refugee

Notes: This table shows how different nationalities, as recorded in the Company House database, are classified into various groups.

Table A8. Classification of Cuisine Types

Category	**Cuisine Types**
UK	Irish, British, Fish & Chip Shops, English, Scottish, Welsh
North America	American
Europe	Austrian, Belgian, French, German, Greek, Hungarian, Italian, Mediterranean, Polish, Portuguese, Russian, Scandinavian, Spanish, Swedish, Swiss, Brasserie, European, Continental, Eastern European, Danish
Middle-East	Lebanese, Iranian, Iraqi, Israeli, Turkish, Middle Eastern, Moroccan, Afghan
South Asia	Indian, Indian Takeaway, Nepalese, Bangladeshi, Pakistani
East Asia	Asian, Chinese, Japanese, Korean, Thai, Vietnamese, Chinese Fast Food, Oriental, Malaysian, Philippine, Indonesian, Mongolian, Tibetan, Burmese, Southwestern
African	African, Sudanese, Mauritian, Egyptian
South America	Argentinian, Brazilian, Colombian, Mexican/Tex Mex, South American, Caribbean, Jamaican, Cuban
Specialty Cuisine	Oceanic, International, Seafood, Vegan, Vegetarian, Kosher
Fast Food	Pizzeria, Fast Food Takeaway, Fast Food Delivery, Pizza Takeaway, Take Away Food Shops, Sandwich Delivery Service
Cafe & Casual Dining	Cafe & Tearoom, Coffee Shops, Juice Bars, Creperie, Internet Cafes
General Restaurant	Restaurant, Bar, Cruises, Other
Culinary Services	Cake Makers, Decorators & Supplies, Caterers

Notes: This table shows the classification of different cuisine types, as recorded in Local Company House or Google Maps, into the broader categories used in our study.

Table A9. Best Subset Selection Results for Platform Rollout Dates

	Food App Rollout Date				
	(1)	(2)	(3)	(4)	(5)
Urban	-52.867	-39.249	-40.297	-36.359	-34.889
	(1.423)	(1.508)	(1.458)	(1.342)	(1.329)
Population 60 older (2001)		404.358	342.134	319.944	298.382
		(17.731)	(17.817)	(15.399)	(15.300)
Share of res. pop. qualification 1 (2001)			298.937	314.579	296.891
			(23.934)	(20.278)	(20.352)
Population				-0.000	-0.000
				(0.000)	(0.000)
GDP					-0.032
					(0.004)
Best Subset				X	
Observations	2307	2088	2088	2021	2012
R-Squared	.375	.491	.526	.654	.665

Notes: This table reports results from OLS regressions. The dependent variable is the rollout date of the earliest platform in months (months since January 1960) for each postal district. Empirical models were selected using BSS. The best subset marked by 'X' indicates the top models selected using BSS on the set of predictors, based on the AIC information criterion. Column 1 shows the best subset across all variables, Column 2 the best subset with two predictors, Column 3 the best subset with three predictors, and so on. Robust standard errors are presented in parentheses.

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