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: technology, entrepreneur, minority, small business, 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, by integrating markets, they might favor large firms that exploit economies of scale. 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 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 platforms 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 discussed forces, lowering entry barriers and market integration, are particularly salient in this context. On one hand, food delivery platforms reduce barriers to entry, which can broaden market access for entrepreneurs. Restaurants need less physical space, do not have to set up their own delivery fleet, and can use the platforms' infrastructure for payments, marketing, customer service, and ordering systems. This lowers initial investments and administrative burdens. If these reduced costs are more evenly distributed across demographics than traditional costs, those who typically face higher barriers, such as marginalized groups, might benefit more, promoting equality in entrepreneurship.

On the other hand, these platforms may increase market concentration. By integrating geographic markets, reducing information asymmetry through ratings and reviews, and using algorithmic sorting, they intensify competition among restaurants. This could lead to a "winner-takes-all" scenario where a few top performers capture most of the market. The net effect of these competing forces remains an empirical question that I address in this study.

To gauge the practical relevance of these forces on restaurant operations, I first explore restaurateurs' own narratives as recorded in online forums. Drawing on posts from Reddit, I extract content discussing food app usage and employ a large language model to analyze reasons restaurateurs cite for using these apps. The most frequently mentioned benefits center around reducing entry and overhead costs, such as less need for prime locations, infrastructure, or dining staff. Descriptive evidence further aligns with this, as app-partnered restaurants typically occupy cheaper and smaller locations within the same neighborhood with smaller dining areas. Guided by these observations, I introduce a theoretical model that explores how the introduction of low-cost technology can stimulate entrepreneurship and broaden consumer choices.

Using the staggered rollout of these platforms, I trace the impact across three interconnected layers—firms, entrepreneurs, and the product market—and organize my empirical findings accordingly.

First, at the firm level, food applications 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 FDA-partnered restaurants exhibit higher productivity—measured by Google Maps ratings—than both non-FDA migrant restaurants and non-migrant FDA restaurants.

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 often have less capital, 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 food delivery apps 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 platforms, 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 platforms. 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) show that e-commerce reduces domestic trade costs by lowering fixed entry barriers and reducing the impact of distance on trade, leading to welfare gains, especially in smaller cities. Conversely, Couture *et al.* (2021) report limited economic benefits from e-commerce expansion in rural China, with gains primarily from reduced living costs for select households. 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 use descriptive evidence to construct a theoretical model that will guide the analysis. Section 4 outlines the research design, focusing on the staggered rollout of food delivery platforms 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 platforms 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. The primary players in the UK in 2024 are JustEat, Deliveroo, and UberEats. JustEat was the first mover, beginning operations in 2006. Deliveroo entered the UK market in 2013, followed by UberEats in 2016.

This paper focuses on UberEats and Deliveroo for two reasons. First, JustEat primarily relied on restaurants to handle their own deliveries, particularly in its early stages. This business model does not introduce the market dynamics that are central to this study. Second, because JustEat did not have its own delivery network, its expansion across the UK was more rapid, without the staggered rollout seen with Deliveroo and UberEats (Keeble *et al.*, 2021), making it less suitable for the type of analysis conducted here.

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 (FDAs).

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 compares 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 FDAs 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 FDA 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 platform 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.

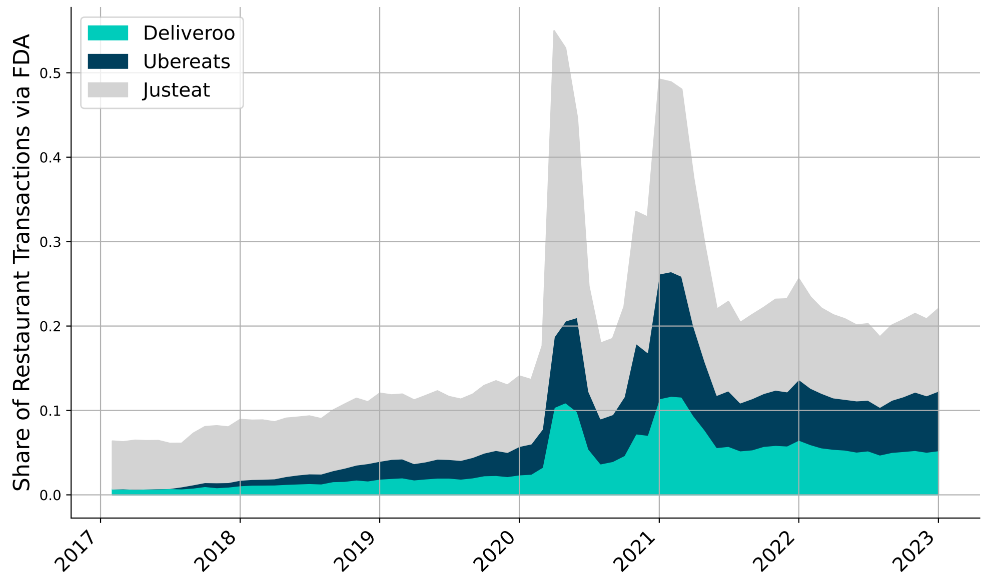
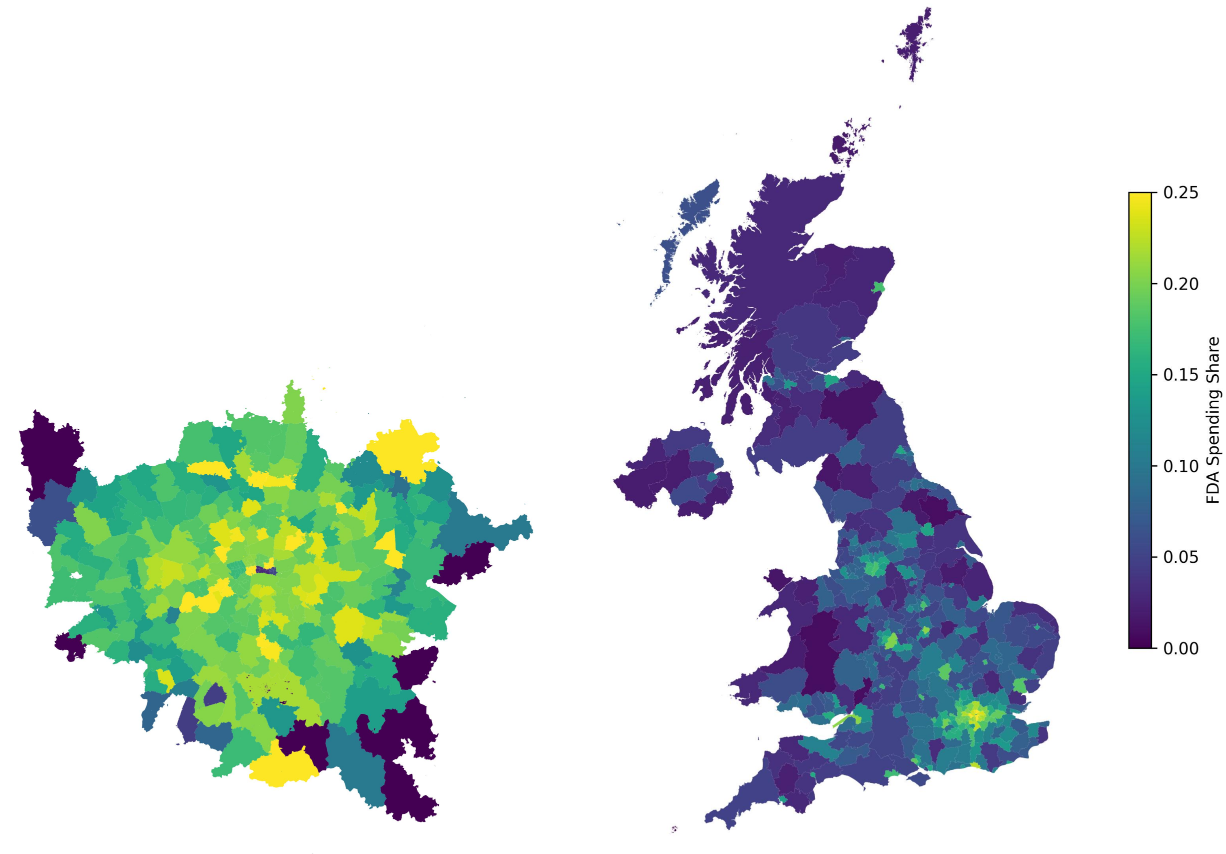


Figure 1. *Notes:* This figure illustrates the trend in the share of transaction values made through various food delivery applications (FDA) from 2017 to 2023. Data is sourced from Fable is limited to transactions in GBP and for MCC codes pertaining to eating establishments. The stacked areas represent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

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 FDA 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 could have been purchased at the same sources as for at-home consumption) and food from restaurants and takeaways. 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). It should be noted that "out-of-home" encompasses all restaurant purchases, including all takeaways, even those that might be eaten at home.

Table A1 provides summary statistics for the Kantar's Worldpanel dataset and compares it with the corresponding population.



(a) Greater London

(b) UK

Figure 2. *Notes:* The figure represents a geographical visualization of the Food Delivery Platform 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 FDA 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.

Looking at demographic patterns, Figure A2 and Figure A3 show how different demographic groups spend on food delivery platforms using a regression. Middle-aged, pre-family households, and London residents tend to spend more on these services.

With respect to usage trends, although most people live in areas with access to FDAs in 2023, actual usage varies. Figure A4 shows that by 2023, just over 20% of the population used FDAs anually. This is down from a pandemic-era high of close to 30%, but much higher than the 9% who used FDAs in 2019. Despite rapid growth, FDAs remain a less common way to access food away from home. Figure A5 shows that between 2017 and 2020, using food apps has been as popular as using restaurant independent delivery. However, there has been a persistent increase in the use of FDAs. A similar trend appears in quarterly spending. Before the pandemic, the average adult spent about £10 per quarter through FDAs (among users, the average was £21). By mid-2023, these amounts rose to around £20 (£39 for users). Figure A6 shows that in 2023, close to 10% of total food spending was through FDAs, slightly higher than the percentage of deliveries made directly by restaurants.

Fable shows a higher share of delivery platform spending compared to Kantar's Worldpanel. Several factors explain this difference. First, Kantar's Worldpanel covers a broader range of purchases, including non-restaurant items like snacks, which dilutes the share of delivery platforms. Second, Fable only captures bank card transactions, so it may overestimate the share of delivery platforms by excluding cash transactions that are more common in non-FDA transactions.

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[1]. An example of the scraped data for each platform is presented in Figure A7. 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. By matching this data for both platform and non-platform restaurants, as detailed in Section A4, I can compare these two groups across these key variables.

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 A8 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 A8 panel (b) showcases a sample of restaurant reviewes listing on Google Maps along with the extracted reviewers names.

[1]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.

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

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 postcode, employment numbers, turnover, industry classification (SIC), legal status (e.g., sole proprietor, partnership), foreign ownership, company start date, and termination date. This rich dataset enables in-depth analysis of both the growth (intensive margin) and number (extensive margin) of businesses.

Due to the anonymized nature of the data, I cannot direclty 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 use the BSD to validate findings from other sources, such as the Local Data Company (LDC). It also offers insights into other industries, enabling placebo and falsification tests. Additionally, comparing BSD data that records registered entities with sources that track restaurant listings can reveal the extent of "virtual" restaurants—those that use one kitchen to prepare food for multiple brands.

Company House. The Company House dataset provides information on business directors, including names, ages, and nationalities. While it does not directly include gender or 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 and gender, 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 notable limitation of the Company House dataset is that it covers only incorporated firms at the establishment level. However, as demonstrated in Table A3, which shows both local units (firms) and enterprises (establishments) from IDBR, this limitation does not significantly constrain the analysis. There are 95,000 local units compared to 79,000 enterprises, with the gap narrowing further when focusing on smaller businesses. In terms of incorporation, there are 79,000 enterprises and 22,000 non-incorporated businesses, again reflecting a manageable difference. While it's important to acknowledge these limitations, the analysis of directors' backgrounds captures the majority of the population. Additionally, since non-incorporated businesses are probably more likely to be immigrant-owned firms, the findings here may actually underestimate the true effects.

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 their 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. Unlike anonymized datasets, LDC's data can be directly matched with other sources at the restaurant level, as detailed in Section A4, enabling firm-level analysis. 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.

2.3. Other Datasets.

I also use the following two 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. [2]

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 FDA 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. This provides data on valuations, total floor area, dining area, and the share of dining area in each postcode. 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 platforms.

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

[2]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.

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 Informed by Evidence

Though it might be assumed that food delivery apps lower entry barriers, verifying this hypothesis through data is crucial. To this end, I start by investigating whether restaurateurs' experiences corroborate the notion that these applications ease entry.

Restaurateurs' Experiences on Reddit: I collected data from the Reddit subreddit *r/restaurateur* and *r/restaurantowners* by extracting posts containing keywords indicative of food delivery applications. This forum serves as a space for restaurant owners and prospective owners to discuss their experiences. Using a large language model—OpenAI's GPT-o1—I analyzed a random sample of 100 posts to identify key topics and motivations mentioned by restaurant owners.[3] From these topics, I created a classification scheme and then instructed the LLMs (`gpt-4o-2024-08-06`) to classify the entire dataset according to this schema.

Figure A9 shows that while, maybe unsurprisingly, expanding reach is the most cited reason for adopting food apps, the other motivations are suggestive of reducing fixed or overhead costs. Categories like Marketing and Visibility (18.2%) and Infrastructure for Workflow (17.6%) suggest that FDAs help restaurants avoid substantial investments in advertising and logistical infrastructure. Similarly, Reduce On-Premise Delivery Costs (13.1%) and Reduce Premises Costs (7.4%) point to savings on physical space and in-house resources, which are typically fixed expenses.

Physical Characteristics of Food App Restaurants: Guided by this finding, I examine the physical characteristics of restaurants that partner with these applications. As shown in Figure A10, I observe that these restaurants are located in cheaper areas, are smaller, and specifically 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. This is consistent with previous evidence, where restaurant owners cited reduced marketing and premises costs as key motivations for using food apps. By relying on app-driven visibility and logistical support, these restaurants can avoid the fixed costs associated with large, high-exposure locations.

Theoretical Model: These observations inform my conceptual framework. I introduce a theoretical model that builds on the principles of occupational choice and market structure from Melitz (2003), incorporates insights from Helpman *et al.* (2004) on firms' FDI decisions, and adapted to the restaurant industry following Fan *et al.* (2018). With this descriptive evidence in mind, I investigate the implications of the introduction of online technology with lowered fixed costs.

3.1. Consumers.

Consider a market with L workers, each supplying one unit of labor. The wage w is determined within the model. The market has two sectors: restaurants (R) and non-restaurants (NR). Consumers have a utility function:

[3] This approach uses LLMs as a modern alternative to traditional topic modeling techniques like Latent Dirichlet Allocation (LDA).

$$U = \prod_{h \in \{R, NR\}} (u_h)^{\beta_h},$$

where u_h is the utility from goods in sector h, and β_h is the expenditure share on sector h.

Each firm ω belongs to one sector and produces a unit measure of varieties, denoted by v. The sub-utility for sector h has a constant elasticity of substitution (CES) form:

$$u_h = \left(\int_{\Omega_h} \int_0^1 q_h(\omega, v)^{(\sigma-1)/\sigma} dv d\omega \right)^{\sigma/(\sigma-1)}, \quad h \in \{R, NR\},$$

where Ω_h is the set of all firms in sector h selling in the region. To simplify, I focus on the restaurant sector and omit the h subscript; the same principles apply to the non-restaurant sector with the exception that e-commerce is not available for the non-restaurant sector.

Using consumer optimization (detailed in Section A5), the demand for a menu item v from restaurant ω, priced at $p(\omega, v)$, is:

$$q(\omega, v) = \beta Y P^{\sigma-1} p(\omega, v)^{-\sigma}, \tag{1}$$

where Y is total spending in the region, and P is the sector's price index:

$$P = \left[\int_{\Omega} p(\omega)^{1-\sigma} d\omega \right]^{1/(1-\sigma)}. \tag{2}$$

The price index P reflects how consumers substitute towards cheaper varieties, lessening the effect of individual price increases. The restaurant's price index $p(\omega)$ is itself a CES aggregator over its menu items:

$$p(\omega) = \left[\int_0^1 p(\omega, v)^{1-\sigma} dv \right]^{1/(1-\sigma)}. \tag{3}$$

Combining equations 1 and 3, the total expenditure on all menu items from restaurant ω is:

$$r(\omega) = \beta Y P^{\sigma-1} p(\omega)^{1-\sigma}.$$

When we introduce quality heterogeneity among menu items, we should think of the $p(\omega, v)$, $p(\omega)$, P, and $q(\omega, v)$ as for each quality unit.

3.2. **Restaurants.** Restaurants compete in monopolistic competition, each offering differentiated menu items. Entry into the industry is free, but potential entrants must pay a fixed cost F_{entry}. The mass of restaurants that pay this cost is M_e. After entering, each restaurant draws a productivity level from a distribution; only those with enough productivity to make positive profits stay in business.

The decision to enter the market depends on expected profitability. Each firm is infinitesimally small, takes aggregate quantities as given, and draws a productivity parameter ϕ from a Pareto distribution:

$$F(\phi) = 1 - \left(\frac{\phi}{\underline{\phi}}\right)^{-\alpha},$$

where α measures the tail heaviness, and $\underline{\phi}$ is the minimum productivity level. A firm with productivity ϕ has a marginal cost of w/ϕ, excluding distribution costs to be discussed later.

Restaurants face CES demand and act as monopolists, setting prices with a constant markup over marginal cost. This ensures full pass-through of productivity gains to consumers. However, marginal costs vary depending on the sales channel—online or offline—which we detail in the following sections.

3.2.1. *Distribution Channels and Associated Costs.* Restaurants can reach customers through two main channels: online (e-commerce) and offline (physical storefronts). Each entails distinct costs that amplify the basic production cost w/ϕ. These costs are modeled as iceberg trade costs, denoted by τ^m, where $m \in E, P$ represents "E-commerce" and "Physical" channels.

In this context, τ^P represents additional costs unique to the dine-in experience, such as washing dishes of in-house customers. On the other hand, τ^E captures costs associated with online sales, including platform fees, delivery logistics, and packaging.

While selling via online platforms typically incurs no fixed cost, setting up a physical store requires a one-time fixed cost f, measured in labor units, not tied to any specific product.[4]. The model assumes no fixed cost for online platforms for simplicity. In reality, there are fixed costs, though typically lower than those for physical stores. This assumption simplifies the model, but similar results would hold with low fixed costs for online sales.

So far, the cost assumptions suggest that each firm will find the marginal cost associated with either online or physical channels profitable for all their items. However, many restaurants utilize both modes to reach consumers. To account for this, I assume firms produce a continuum of varieties or menu items. For each menu item, there are unique consumer preference draws for online or offline sales. This allows some items to be more suited to one channel than the other, leading to the possibility that restaurants adopt a hybrid strategy to maximize profitability.

Specifically, for each menu item v, consumers have independent taste shocks (v^E, v^P) for online and offline channels. A physical unit of a product translates into v^E quality units online and v^P quality units offline. Thus, the marginal cost to deliver one quality unit is $\frac{w\tau^E}{\phi v^E}$ for online and $\frac{w\tau^P}{\phi v^P}$ for offline. Firms choose the lower-cost option for each variety.[5] Following Fan *et al.* (2018), I assume independent taste shocks for each product variety and sales channel, drawn from a common Fréchet distribution with the CDF:

$$F(v) = \exp(-v^{-\theta}) \tag{4}$$

[4]Conceptually, this fixed cost can include both recurring overhead costs (e.g., rent, property taxes, and staff salaries) and one-time sunk costs (e.g., interior design). This is because this model ignores transitional dynamics, focusing solely on steady-state operations.

[5]This can also reflect the variation in consumer inclination towards online versus offline purchasing channels. Based on this interpretation, the distribution of (v^E, v^P) across a firm's product varieties can be interpreted as a representation of the distribution of consumer preferences in a region for a restaurant's products.

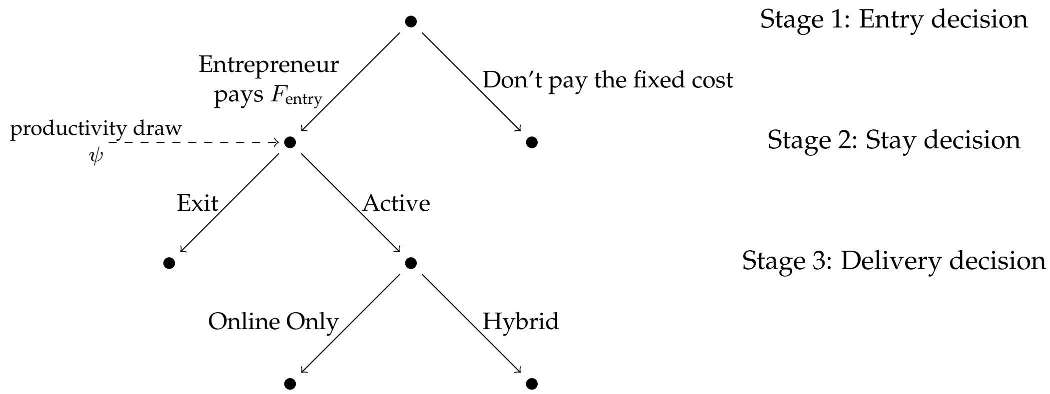


Figure 3. *Notes:* This figure shows a schematic representation of the decision-making process for firms adopting delivery technology. It outlines the sequential stages entrepreneurs go through, from entry decisions and staying active in the market to choosing between delivery options and deciding on platform sign-up.

In the rest of this section, I compare the equilibrium before and after the introduction of e-commerce platforms. Before e-commerce, online sales were not an option, so firms' only option was to pay the fixed cost f^P and bear the marginal cost τ^P to operate. With the advent of e-commerce, firms can now choose to sell online, offline, or through both channels.

3.3. Before E-commerce.

Before e-commerce, firms could only sell through physical stores. The marginal cost of preparing and delivering a menu item was $\frac{w\tau^P}{\phi v^E}$. The cumulative distribution function (CDF) of this marginal cost for physical-only restaurants is:[6]

$$G^{pre-E}(c) = 1 - \exp\left(-\left(\frac{\tau^P w}{\phi}\right)^{-\theta} c^{\theta}\right),$$

In monopolistic competition with CES utility, firms charge a uniform markup of $\frac{\sigma}{\sigma-1}$ over marginal cost for all products. So, the price for each menu item is $\frac{\sigma}{\sigma-1}\frac{w\tau^P}{\phi v^P}$. Therefore, the restaurant's price level is:

$$p^{pre-E}(\phi) = \frac{\kappa^{\frac{1}{1-\sigma}} w\tau^P}{\phi}$$

where κ is a constant defined as $\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$. The total revenue for a restaurant with productivity ϕ is:

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[6]The CDF of $c = \frac{\tau^P w}{\phi v^E}$, where v^E follows the distribution $F(v^E) = \exp(-v^{-\theta})$, is derived as follows

$$G(c) = \mathbb{P}(C \leq c).$$

This can be expressed in terms of v^E as:

$$G(c) = \mathbb{P}\left(\frac{\tau^P w}{\phi v^E} \leq c\right) = \mathbb{P}\left(\frac{\tau^P w}{\phi c} \leq v^E\right) = 1 - F\left(\frac{\tau^P w}{\phi c}\right) = 1 - \exp\left(-\left(\frac{\tau^P w}{\phi c}\right)^{-\theta}\right).$$

$$r^{pre-E}(\phi) = \kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^P\right)^{1-\sigma} \phi^{\sigma-1}$$

Thus, the profit for a firm with productivity ϕ before e-commerce is:

$$\pi^{pre-E}(\phi) = \frac{1}{\sigma}\kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^P\right)^{1-\sigma} \phi^{\sigma-1} - wf^p$$

A restaurant will decide to operate if its profit is positive. The cutoff for this decision, ϕ^a, is:

$$\phi^a = \left(\frac{\kappa\beta Y}{\sigma w f^P}\right)^{\frac{1}{1-\sigma}} \frac{w}{P}\tau^P \tag{5}$$

3.4. **After E-commerce.** With e-commerce, restaurants have more choices. Beyond the traditional dine-in model, they can operate fully online or adopt a hybrid approach. Before calculating profits for each model, it's important to understand the strategic factors influencing a restaurant's choice.

Assuming zero fixed costs for online sales, establishing an online presence is costless. Therefore, all restaurants will choose to operate online, either exclusively or alongside a physical store.[7]

Some restaurants find it optimal to maintain a physical storefront because having both channels can offer additional benefits. When taste shocks for online and offline modes are equal, and $\tau^P < \tau^E$, the physical channel is cheaper. More generally, access to both modes allows restaurants to better cater to consumer preferences, potentially leading to higher profits by meeting diverse customer tastes. The following sections will discuss the decision of online-only or hybrid—in for restaurants.

3.4.1. *Online-only Restaurants.* Online-only restaurants[8] operate entirely through online delivery platforms without maintaining any physical dine-in locations. They rely solely on the digital marketplace to reach customers and deliver their menu items.

The marginal cost of preparing and delivering a menu item is $\frac{w\tau^E}{\phi v^E}$. The cumulative distribution function (CDF) of this marginal cost is:

$$G^{ON}(c) = 1 - \exp\left(-\left(\frac{\tau^E w}{\phi}\right)^{-\theta} c^\theta\right),$$

Since firms charge a constant markup over marginal cost, the price for each menu item is $\frac{\sigma}{\sigma-1}\frac{w\tau^E}{\phi v^E}$. Therefore, the restaurant-level price index is (derived in Section A5):

$$p^{ON}(\phi) = \frac{\kappa^{\frac{1}{1-\sigma}} w\tau^E}{\phi} \tag{6}$$

The total sales for a restaurant with productivity ϕ are:

[7]In practice, some restaurants, particularly high-end establishments, opt out of online platforms to preserve their exclusive in-person experience. Smaller eateries might avoid online platforms due to digital illiteracy or operational limitations. Introducing some fixed costs for online sales can account for firms that choose to remain exclusively physical. However, I have not included this in the model because these considerations fall outside the scope of this paper, which focuses on the interaction between online and offline sales. Also, platform fixed costs are generally much lower than those of operating a physical storefront.

[8]These restaurants are also known as dark kitchens, ghost kitchens, or virtual restaurants.

$$r^{ON}(\phi) = \kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1} \tag{7}$$

Consequently, the profit for an online-only restaurant is:

$$\pi^{ON}(\phi) = \frac{1}{\sigma} r^{ON}(\phi)$$

3.4.2. *Hybrid Restaurants.* Hybrid restaurants [9] use both online and offline channels. For each menu item, they choose the channel with the lower unit cost, given by $\min\left(\frac{w\tau^E}{\phi v^E}, \frac{w\tau^P}{\phi v^P}\right)$.

Given the Fréchet distribution of taste shocks (Equation 4), the CDF for the marginal cost across menu items for a hybrid restaurant is (detailed derivation in Section A5):

$$G^{HF}(c) = 1 - \exp\left(-\sum_{m\in\{E,P\}} \left(\frac{w\tau^m}{\phi}\right)^{-\theta} c^\theta\right).$$

For each menu item, the restaurant charges a markup of $\frac{\sigma}{\sigma-1}$ over marginal cost. The aggregate restaurant-level price index (detailed derivation in Section A5) is:

$$p^{HF}(\phi) = \frac{\kappa^{\frac{1}{1-\sigma}} w}{\phi} \left(\sum_{m\in\{P,E\}} (\tau^m)^{-\theta}\right)^{-\frac{1}{\theta}} \tag{8}$$

The total sales of a hybrid restaurant are:

$$r^{HF}(\phi) = \kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\sum_{m\in\{P,E\}} (\tau^m)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} \phi^{\sigma-1} \tag{9}$$

This shows that more productive restaurants (higher ϕ) generate greater sales. The profit, after deducting the fixed cost f^P for the physical location, is:

$$\pi^{HF}(\phi) = \frac{1}{\sigma} r^{HF}(\phi) - w f^P$$

When the cost of e-commerce delivery decreases (lower τ^E), total restaurant sales increase, as indicated by Equation 9. However, this boost in online sales is partly offset by a decline in offline sales, as items previously sold offline become more competitively priced online. The degree of this substitution effect depends on the parameter θ.

3.4.3. *Channel choice.* Restaurants can choose from three models: online-only, hybrid, and physical-only. The profit functions are:

- Online-only Restaurants:

$$\pi^{ON}(\phi) = \frac{1}{\sigma} \kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1}$$

[9]These include establishments that offer dine-in services alongside online delivery via platforms like Uber Eats or Deliveroo. This category also includes large chains such as McDonald's and Starbucks, which often supplement their delivery fleet with platform presence.

- Hybrid Restaurants:

$$\pi^{HF}(\phi) = \frac{1}{\sigma}\kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta} \right)^{-\frac{1-\sigma}{\theta}} \phi^{\sigma-1} - w f^P$$

- Physical-only Restaurants:

$$\pi^{PY}(\phi) = \frac{1}{\sigma}\kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^P\right)^{1-\sigma} \phi^{\sigma-1} - w f^P$$

The physical-only model is always less profitable than the hybrid model, so the real decision is between the hybrid and online-only models. A restaurant will choose to operate a physical store if the additional profit from operating a physical location justifies the fixed cost of establishing it, i.e., if the profit from the hybrid model exceeds the profit from the online-only model.

Figure 4 illustrates the profit functions of Online-Only (ON) and Hybrid Firms (HF) relative to their productivity levels. The graph shows that Hybrid restaurants experience a steeper increase in profits with higher productivity[10], but they must first cover the fixed cost of a physical store. This fixed cost creates a productivity threshold, above which firms can afford to operate as Hybrid Firms. Below this threshold, firms remain Online-Only, as their profits do not justify the additional fixed cost.

The productivity cutoff ϕ^*, derived in detail in Section A5, is expressed as:

$$\phi^* = \left(\frac{\kappa\beta Y}{\sigma w f^P}\right)^{\frac{1}{1-\sigma}} \frac{w}{P} \left[\left(\sum_{m\in\{P,E\}} (\tau^m)^{-\theta} \right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{10}$$

More productive restaurants are more likely to invest in a physical store, as their higher revenue potential allows them to cover fixed costs more easily. Also, when e-commerce is not available, i.e., τ^E goes to infinity, the cutoff in Equation 10 converges to the pre-e-commerce cutoff in Equation 5, reflecting the pre-e-commerce scenario.

3.4.4. *Free Entry Condition.* To enter the market, firms pay an initial setup cost F_{entry} in labor units. The following free entry condition ensures that expected profits equal this entry cost:

$$\int_{\underline{\phi}}^{\phi^*} \pi^{ON}(\phi) dF(\phi) + \int_{\phi^*}^{\infty} \pi^{TC}(\phi) dF(\phi) = w \cdot F_{\text{entry}} \tag{11}$$

I substitute equation 10 into equation 11 (detailed in A5) to rewrite the free entry condition:

$$\left(\frac{\sigma-1}{1+\alpha-\sigma}\right)\left(\frac{\underline{\phi}}{\phi^*}\right)^{\alpha} + \left(\frac{\left(\tau^E\right)^{1-\sigma}}{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma} \right) \left(\frac{\underline{\phi}}{\phi^*}\right)^{\sigma-1} = \frac{F_{\text{entry}}}{f^P}. \tag{12}$$

[10] This follows from the fact that $\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} > \left(\tau^E\right)^{1-\sigma}$. To see this, note that raising both sides to the power of $-\frac{\theta}{1-\sigma}$ simplifies the inequality to $\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta} > \left(\tau^E\right)^{-\theta}$. Since $\left(\tau^P\right)^{-\theta} > 0$, the inequality holds.

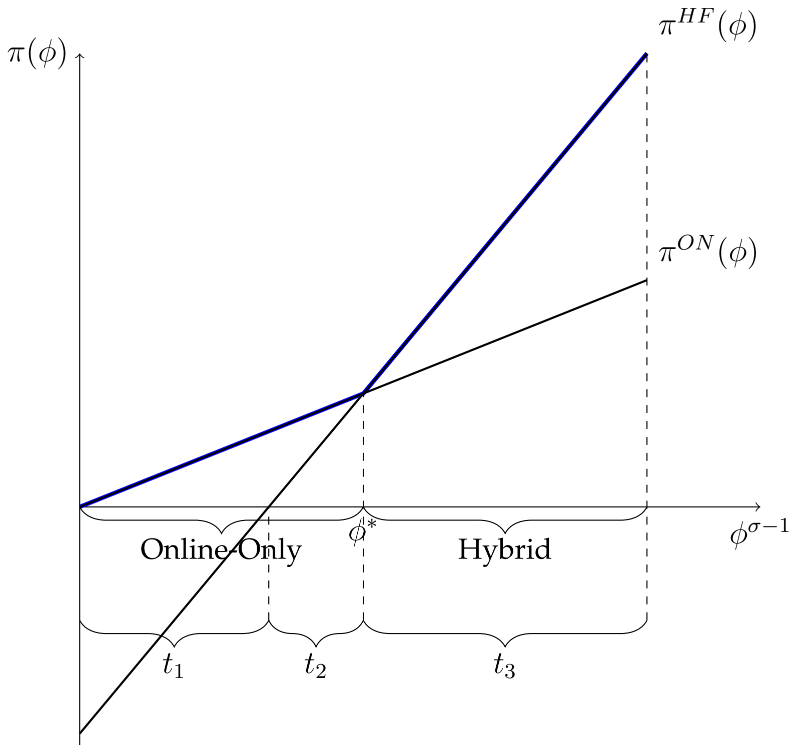


Figure 4. *Notes:* This figure shows a schematic representation of profits and optimal actions for restaurants with a given productivity.

The left-hand side is a strictly decreasing and continuous function of ϕ^*. It approaches infinity as $\phi^* \to 0$ and zero as $\phi^* \to \infty$. The right-hand side is a positive constant. Therefore, by the intermediate value theorem, there is a unique solution for ϕ^*.

3.5. **General Equilibrium.** In general equilibrium, we determine the survival productivity threshold ϕ^*, the wage w and its supply L^h, the number of new entrants M, and the total expenditure Y. To close the model, we ensure labor market equilibrium: total labor demand equals total labor supply.

$$L = \sum_h L^h \tag{13}$$

where labor demand in each sector h is comprised of three components. The first component reflects the variable labor used in production.[11]. The second component accounts for labor needed to set up physical stores, while the third reflects labor demand arising from labor for fixed entry costs.

[11] The variable input in production can be determined by expressing total revenue as the sum of profits and costs: $S = \pi + \text{total cost} = \pi + f^P + \text{variable labor cost}$. Given the profit equation $\pi = \frac{S}{\sigma} - f^P$, the variable labor cost can be derived as $S - \frac{S}{\sigma} = \frac{\sigma-1}{\sigma} S$. Therefore, the corresponding labor input, in terms of the number of workers employed, is $\frac{\sigma-1}{\sigma}\frac{S}{w}$, where w denotes the wage rate.

$$L^h = \underbrace{\frac{\sigma - 1}{\sigma} M^h \left[\int_{\phi}^{\phi^*} \frac{s^{ON}(\phi)}{w} \, dF(\phi) + \int_{\phi^*}^{\infty} \frac{s^{TC}(\phi)}{w} \, dF(\phi) \right]}_{\text{Variable input in production}}$$
$$+ \quad \underbrace{f^P M^h \int_{\phi^*}^{\infty} dF(\phi)}_{\text{Labor needed for physical stores}} \tag{14}$$
$$+ \quad \underbrace{M^h F_{\text{Entry}}}_{\text{Labor demand for firm entry}} \quad .$$

Since profits are zero in equilibrium, total income equals total labor earnings:

$$Y = wL \tag{15}$$

3.6. **Impact of E-commerce.** I can now analyze the impact of e-commerce by comparing equilibria before and after its adoption, focusing on steady-state equilibria to capture long-term consequences. I will prove in Section A5 that the transition from a pre-e-commerce world to one with e-commerce results in:

(a) All firms, regardless of their productivity level ϕ, now operate.
(b) The productivity cutoff for online operation, ϕ^* (equation 10), would be higher than the offline cutoff, ϕ^a (equation 5), leading some previously offline firms to shift to exclusively online operations.
(c) The overall mass of firms, M, increases.
(d) Consumer utility, measured by the real wage w/P, increases.

4. RESEARCH DESIGN AND ROLLOUT OF PLATFORMS

To examine the impact of food delivery platforms 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:

$$y_{st} = \alpha + \Sigma_j \beta_j \mathbb{1}[t = E_s + j] + \mu_s + \lambda_t + X_s \times \lambda_t + \epsilon_{st} \tag{16}$$

This approach compares the pre- and post differences in outcomes between regions (or individuals residing in regions) where a food delivery platform was introduced and those in regions where the food delivery platform 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 the FDP for individuals or the restaurant sector.

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. As shown in Figure 5, denser urban areas gained access to both major food delivery platforms earlier than less densely populated regions, indicating that the rollout was 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. Moreover, evidence suggests that the staggered expansion resulted from level factors rather than trends in outcome variables. Factors influencing the rollout include: first, establishing an office to manage services in nearby locations incurs a fixed cost, meaning the market must be sufficiently dense to justify the initial rollout, which causes larger and denser areas to be prioritized. That is, upfront investments are justified only in regions with sufficiently-large local demand. Second, scale constraints due to limited platform capacity, especially at the onset, influenced the sequence. Third, platforms aim to reinforce network effects by simultaneously attracting sufficient users and restaurants, which is 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 A6, 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 five measures to address concerns about the parallel trends assumption. First, while difference-in-differences regression results are presented in the appendix, I estimate a dynamic version of Equation 16 in the main analysis using the estimators from Borusyak *et al.* (2024) to detect any pre-trends. Second, in the robustness section, I estimate dynamic versions of the alternative estimators introduced by De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). Third, I include indicators for local economic activity to account for different trends based on the local economic situations of various regions. Fourth, I conduct a robustness check by including rollout-group-level linear time trends to account for any linear trends. Finally, I analyze placebo industries and find no significant results.

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 platforms. 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. 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.

As mentioned, the main estimator used will be that of Borusyak *et al.* (2024) because TWFE models, despite their popularity, can yield biased and inconsistent estimates when treatment effects vary by group or over time. This occurs due to its methodology, as outlined by Goodman-Bacon (2021), which averages effects from various 2×2 group-time comparisons and assigns weights that can sometimes be negative. Specifically, this problem stems from comparing the late treatment group (as the treatment group) with the early treatment group (as the control group). Even with the parallel trends assumption, if treatment effects vary over time, the early treatment group does not serve as a valid control (or counterfactual) for the late treatment group.

Recent methodological advances emphasize the importance of approaches that can handle heterogeneous treatment effects. Concerns about the reliability of the TWFE estimator can be addressed by replicating results using robust estimators developed by De Chaisemartin and d'Haultfoeuille (2020), Borusyak *et al.* (2024), Goodman-Bacon (2021), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). These estimators avoid the problematic 2×2 difference-in-differences comparisons between newly treated and previously treated units, providing consistent estimates despite treatment effect heterogeneity across time and groups. In my main results I will report Borusyak *et al.* (2024) estimator, while the robustness section reports results using other alternative estimators.

4.1. **Defining Market.** Defining geographic markets in the context of food delivery platforms 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 platforms define their delivery areas, making them a useful unit of analysis. Given these strengths and weaknesses, where possible, 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 platform 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 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.[12] 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 A11 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 specific specific regions. 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 5 show Deliveroo's and UberEatsr rollout across postal districts, highlighting considerable spatial variation. Appendix Figure A12 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 A13 further explores this by directly comparing the rollout dynamics of both platforms, highlighting areas served exclusively by one or neither platform.

The steady expansion of food delivery platforms has significantly increased their geographic and population reach over time. Figure A14 illustrates the coverage of postal districts and local authorities by UberEats or Deliveroo over time. Panel (a) shows a steady increase in postal district

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

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 A15 combines platform rollout dates with postal district population data, illustrating that by 2023, nearly 90% of the population had access to at least one platform-affiliated restaurant.

4.2.3. *Addressing Concerns of Market Boundaries and Accessibility.* As mentioned, one concern in this context is assigning a postal district or local authority as a control group based on the absence of an FDA restaurant in that spatial unit, while residents in that area may still access FDA restaurants in neighboring units. Conversely, areas may be marked as treated simply because a single restaurant joined the platform in that unit, which may not reflect true accessibility for all residents. Although I cannot check that every postcode in treated areas had access to FDAs, I implemented three approaches to demonstrate that, on average, this is not a significant concern:

First, in Figure A16, I show the pattern of restaurant sign-ups on food delivery platforms following their rollout, with a notable spike in the initial phase, followed by more restaurants joining over time. This confirms that rollouts generally involve onboarding multiple restaurants, not just a single establishment.

Second, as a robustness check for Deliveroo, where restaurant presence determines treatment versus control regions, I redefined the rollout in a postal district by identifying the earliest time a 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.[13]

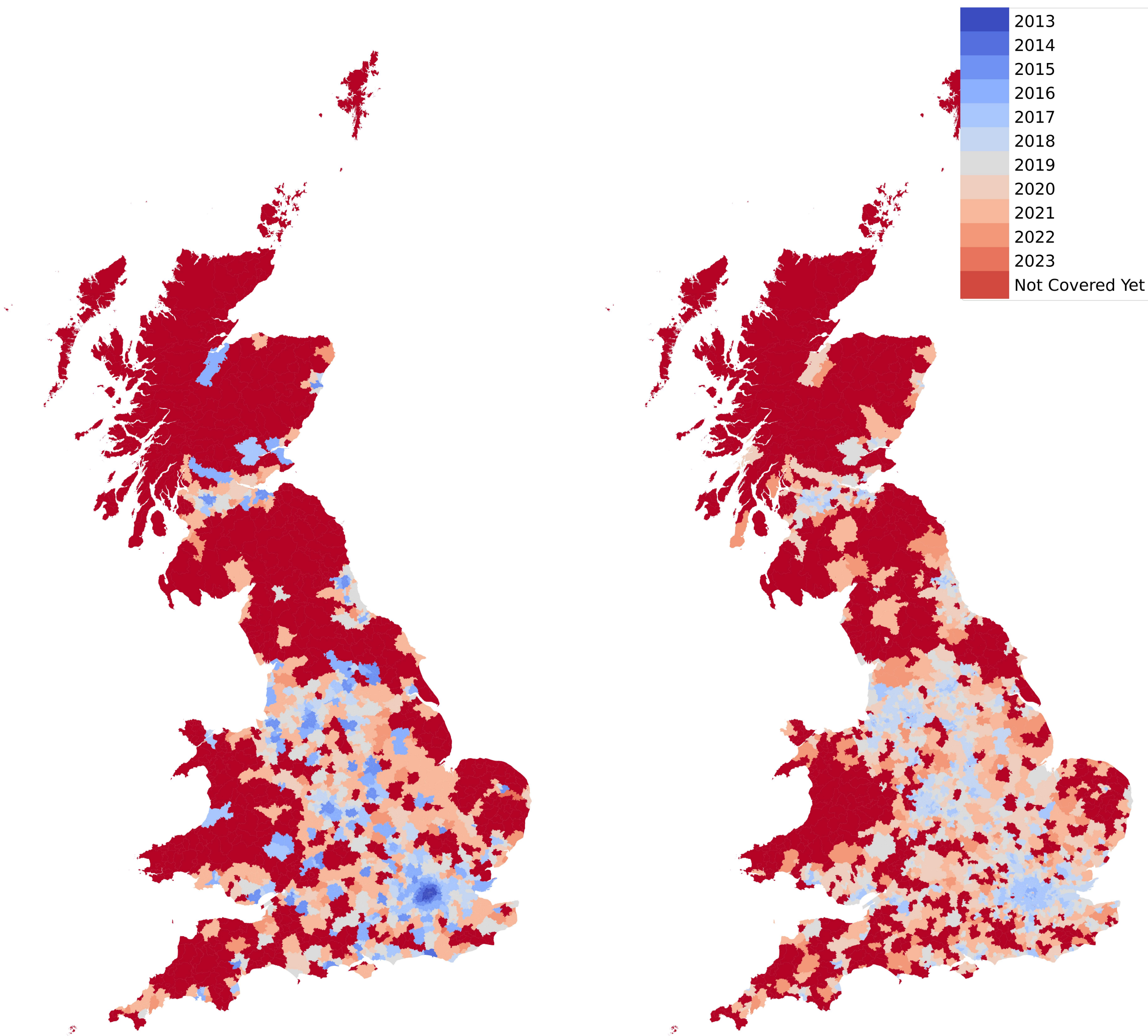
Third, I assessed restaurant accessibility on both platforms across all UK postcodes, comparing postcodes in treated regions with those in control. Figure A17 confirms that treated postcodes have significantly higher accessibility, particularly at greater distances. When defined at the local authority 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 FDA restaurant. Figure A18 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 further validate that the platform rollout measure reflects not only access but also actual consumer usage, I conduct an event study, regressing food delivery spending on the staggered rollout measure using data from both the Fable and Kantar's Worldpanel datasets, as specified in equation 16.

Figure A19 shows the impact of the rollout of food delivery platforms on spending using the Fable dataset. The results are reassuring, suggesting that the timing of the platform rollout aligns

[13]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.



(a) Deliveroo Rollout

(b) UberEats Rollout

Figure 5. *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.

well with the pattern of spending on these platforms. This confirms that the measure of platform rollout accurately captures variations in consumer access and usage of food delivery applications.

Figure A20 shows the same result using Kantar's Worldpanel dataset, attesting to the alignment of my metric with the actual usage of food delivery platforms.[14]

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 platforms around the same time.

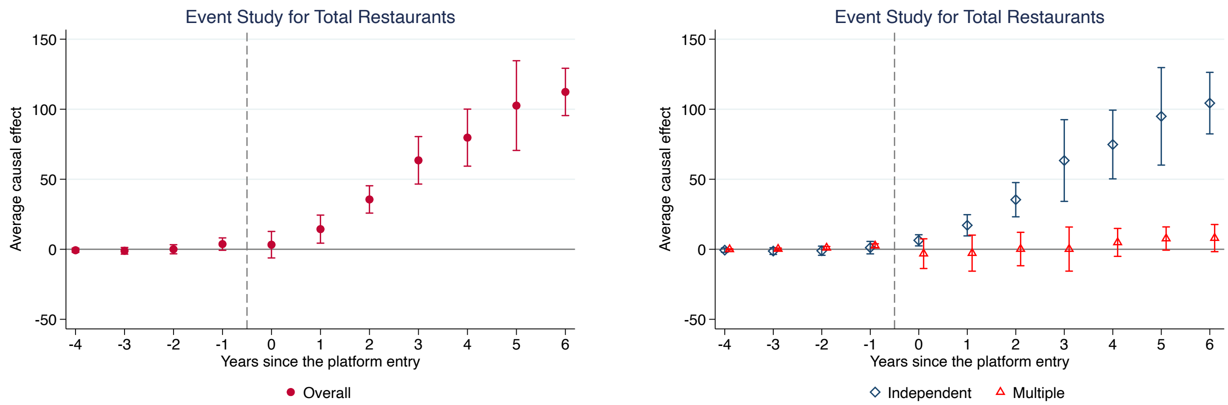
In this chapter, I outlined the methodology for defining the market and pinpointing the rollout dates of the platforms. I showed that individuals in regions identified as having access to the platforms indeed have access to multiple restaurants. Furthermore, I used two spending datasets and showed my 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 and consumers.

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. I also explore underlying mechanisms and investigate the barriers in traditional brick-and-mortar settings that are potentially mitigated in an e-marketplace environment. Finally, I investigate the extent to which these impacts trickle down to the product market, influencing the variety of cuisines available to consumers.

5.1. **Impact on Firms: Restaurant Market Dynamics and Industry Expansion.** I assess the impact of food delivery apps on restaurant numbers using multiple datasets. Figure 6 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 a 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 Data Company (LDC) and control for local authority and year fixed effects, as well as interactions between local GDP and population by year.

[14]The Kantar's Worldpanel dataset indicates approximately half the level of food delivery platform consumption compared to the Fable dataset. Several factors may contribute to this discrepancy. For example, Kantar's Worldpanel's inclusion of categories such as "collected yourself" may capture some orders fulfilled through delivery platforms, artificially reducing recorded food delivery consumption.



(a) Overall

(b) Independent vs Multiple

Figure 6. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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).

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 16 is specified and estimated in levels (although log transformations are still presented in Figure A21 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.,

$$\hat{y}_{st} \equiv \sum_k \hat{\lambda}_k \cdot I[k = t] + \sum_l \hat{\mu}_l \cdot I[l = s]. \tag{17}$$

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 A22, this model reveals a 35% increase in the number of firms.

One potential 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 16, 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.

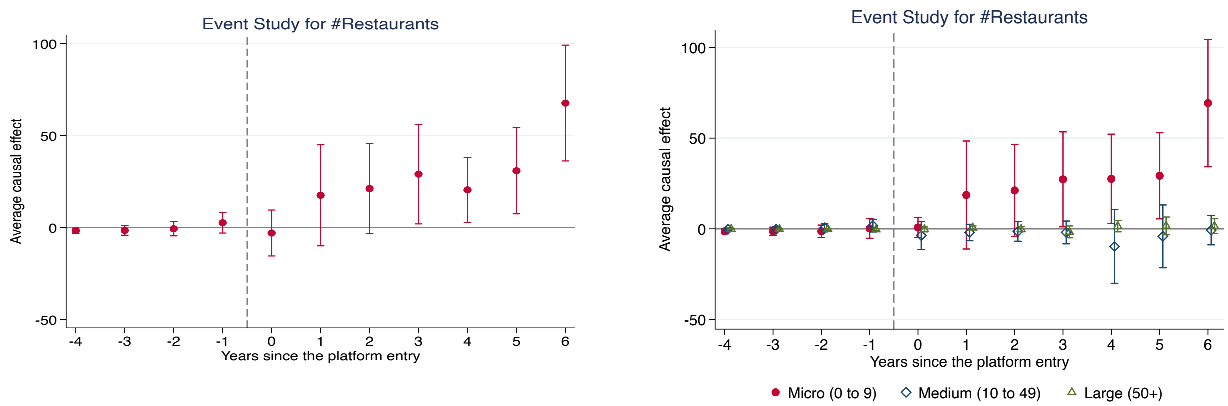
In addition, I run several robustness checks in Figure A23, to confirm the validity of the results. These checks include excluding local authorities in London, removing the COVID-19 period from the analysis, and winsorizing the data at the 5th and 95th percentiles. The findings remain robust across all specifications. Additionally, I estimate the model using alternative difference-in-differences estimators, which yield broadly consistent outcomes.

FDAs 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 FDAs do not necessarily rely exclusively on these platforms. Even a modest additional revenue from FDAs can make opening a restaurant profitable. Second, and more importantly, FDAs most likely have led to the proliferation of small or niche restaurants that, while accounting for a small share of sales, greatly contribute to the total number of establishments.

To assess whether FDAs disproportionately benefit small restaurants, Figure 7 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 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 platforms. 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.

To validate the exogeneity of the staggered rollout design, Figure A24 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. To address concerns about cherry-picking placebo industries, Figure A25 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.

5.1.1. *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 platforms stimulate additional spending, thereby expanding the market. The introduction of food delivery platforms 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.



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

Figure 7. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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..

To investigate this, I use Kantar's Worldpanel data and apply the same specification as in Equation 16, incorporating individual spending with fixed effects. The results in Figure A26 show that FDA 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 services are expanding the overall market. For instance, consumers may order delivery during bad weather when they would otherwise stay in. This finding aligns with the earlier evidence of market expansion, where the growth in the number of restaurants is driven by rising consumer demand.

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 platforms 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 8 shows that both openings and closures have risen, likely due to heightened competition as food delivery platforms 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 A27). This suggests that while some restaurants exit, the reduced barriers to entry provided by food delivery platforms—through delivery logistics, marketing, and payment systems—help new entrepreneurs enter the market, more than offsetting the rise in closures.

I also use Companies House data to examine entry and exit, serving two purposes. First, it validates the earlier results with official administrative records. Second, It is important to verify

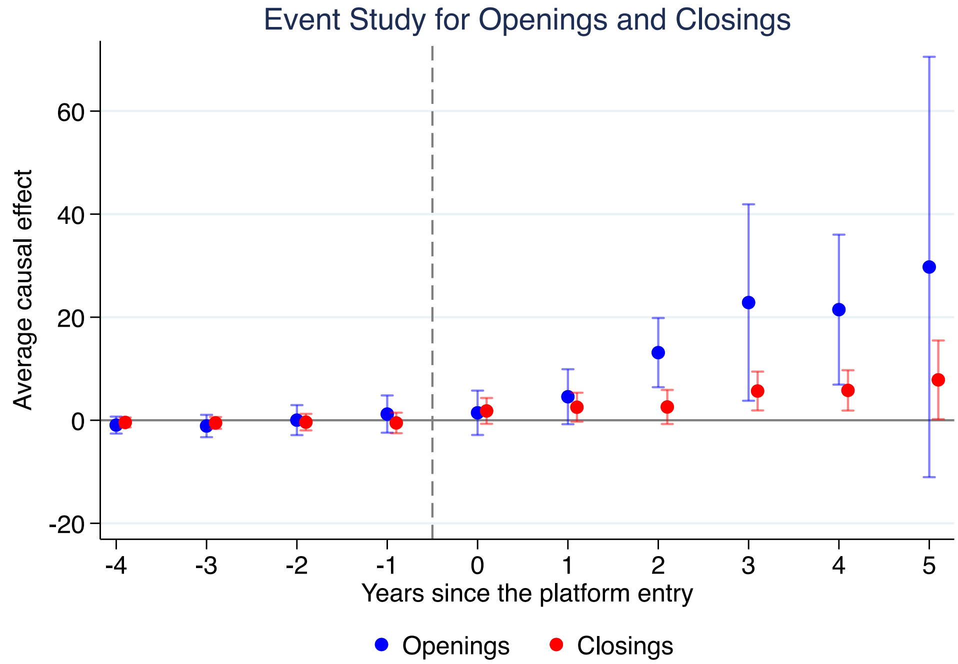


Figure 8. *Notes:* This figure presents the impact of food delivery platforms on the number of restaurant closings and opening per year across Local Authority Districts (LADs). The analysis controls for postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

that the results remain consistent in this dataset, as I will later use it to analyze the backgrounds of entrepreneurs. The result is depicted in Figure A28. The similarity of results for the number of firms (enterprises) using Companies House data and the number of establishments (local units) using LDC data reinforces the idea that food delivery platforms primarily facilitate the entry of independent, single-location restaurants (establishments), while having a lesser impact on the expansion of multi-location chains or enterprises.

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 A29 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.

5.2. **Impact on Entrepreneurs: Uneven Entrepreneurial Success Across Demographics.** This section examines which demographic groups benefit the most from food delivery platforms. 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 A30, 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.[15]

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 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 FDAs mitigate these disparities? Potentially, yes. In the theoretical framework, setting up a physical establishment involved uniform fixed cost barriers, while food delivery platforms offered lower fixed costs, encouraging more entrepreneurship and leading to the creation of more firms, as observed in previous empirical analyses. However, food delivery platforms 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, FDAs can limit discrimination and ease language barriers. They lower fixed costs, alleviating challenges related to raising capital and securing leases. FDAs 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.

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

5.2.1. *Minority Representation in FDAs.* To explore whether restaurateurs from minority backgrounds are more likely to use FDAs, 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 is Section A4. Once matched, After matching, I inferred the backgrounds of restaurant directors based on their names.

Figure A31 panel (a) shows that minority groups are more represented among restaurants partnered with food delivery platforms, where backgrounds are inferred from first and last name. British directors, who are the majority of all restaurant directors, are underrepresented in Deliveroo and UberEats-partnered restaurants. In contrast, minority groups such as Muslim, European, South Asian, East Asian, and African directors are more prominently represented. This finding is confirmed when analyzing nationality, as shown in panel (b).

There may be concerns that the matched sample of Deliveroo and UberEats restaurants is not representative of all restaurants on these platforms, possibly due to minority-owned restaurants being easier to match. However, this is unlikely; 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-owned 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.

5.2.2. *FDAs' Impact on Minority Entrepreneurs.* I analyze the causal impact of food delivery platforms 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:

$$y_{g,s,t} = \alpha + \sum_{g} \beta_g D_{st} \times \mathbb{I}(g) + \mu_s + \lambda_t + X_{s,t} \times \lambda_t + \epsilon_{g,s,t} \tag{18}$$

Figure 9 reveals significant variation in the platform's impact on different backgrounds, with entrepreneurs with African and Muslim-sounding names benefiting the most. This suggests that food delivery platforms 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 A32 shows that immigrant entrepreneurs from the Middle East and Africa benefit the most, while European and British entrepreneurs benefit the least.

Figure 9. *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.

I further analyze the impact on entrepreneurs by gender and age. The appendix Figure A33 shows no statistically significant difference in platform impact on female entrepreneurs compared to male entrepreneurs. Figure A34 reveals opportunities across all ages, but the impact seems to diminish for older age groups. This could imply that younger people face more barriers in traditional restaurant operations, and the platforms help level the playing field. Additionally, younger entrepreneurs might adapt more quickly due to their digital literacy. Interestingly, a significant positive impact on the 60+ age group is also observed, although very noisy. This suggests a potential U-shaped relationship where younger entrepreneurs with digital fluency and older entrepreneurs with experience or capital benefit the most from the platforms.

5.3. **Mechanisms Behind Differential Entrepreneurial Impact.** I investigate why food delivery platforms disproportionately benefit minority entrepreneurs. While it is challenging to 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. First, they might have been less productive in the past, and the high barriers to entry kept them out. Now, with lower barriers, they can enter. Second, they may have faced higher barriers than others, but they were not less productive. Reducing and harmonizing these barriers would allow them to participate more. 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 explanation suggests a need for policies focused on improving productivity through training and resources. The second implies a focus on removing barriers or reducing discrimination.

Table A6 shows that minority-owned restaurants on the platform are not less productive than minority non-FDP or non-minority FDP restaurants, where productivity is measured by average Google reviews. This finding, based on data matched from Companies House, Google Maps, and listings from UberEats and Deliveroo, suggests that the second explanation is more likely—minorities were previously held back by higher barriers, and now those barriers have been reduced.

So, what were these barriers? There are two major barriers in traditional settings that may affect minorities more: discrimination or disadvantage in face-to-face interactions and capital constraints, which make it hard for them to afford expensive locations. To explore this, I first analyze whether changes in the racial makeup of customers contribute to the benefits. Next, I look at whether operating in lower-cost areas plays a role.

5.3.1. *Racial Composition of Consumers.* I analyze customer reviews from Google restaurant listings to infer the racial background of customers based on their names. That is, for each restaurant, I compile the set of reviewers and infer their backgrounds to estimate the racial composition of the customer base. I then compare FDA restaurants with non-FDA ones and, within FDA-partnered restaurants, I distinguish between FDA and offline orders.

I find that the racial makeup of customers remains consistent across FDA-partnered and non-partnered restaurants, as well as between FDA and offline customers of FDA-partnered establishments, regardless of the ethnic cuisine offered. Figure A35 illustrates this non-parametrically, with the bars showing that the racial profile of customers for non-FDA restaurants, FDA restaurants, and FDA orders are nearly identical.

This evidence suggests that FDAs do not primarily benefit minority-owned businesses by helping them reach new racial demographics. For instance, the argument that FDAs 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 FDAs enable minority-owned 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-owned restaurants probably reach a wider geographic customer base using food apps, but not a different demographic one. Instead, FDAs likely reduce structural barriers that minorities face in the restaurant industry.

5.3.2. *Heterogeneous Impact in Cheaper and More Deprived Regions.* I examine whether FDAs 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:

$$y_{s,j(s),t} = \alpha + \sum_{j=1}^{4} \beta_j D_{st} \times \mathbb{I}\left[j(s) = j\right] + \mu_s + \lambda_t + X_s \times \lambda_t + \epsilon_{s,j(s),t} \tag{19}$$

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

Figure 10 highlights the differential impact of food delivery platform 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. This suggests that food delivery platforms help minority entrepreneurs open businesses in affordable areas by lowering entry barriers.

A likely explanation is that minority entrepreneurs often face credit constraints and higher barriers to entry in high-rent areas. FDAs 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 like rent. This explains why non-White British entrepreneurs see a larger positive impact in less expensive areas.

The analysis uses the Company House dataset to infer director backgrounds, but it has limitations. It does not cover unincorporated businesses and uses registered addresses rather than trading ones. To address this, I use LDC data, which includes both incorporated and unincorporated businesses and is based on trading addresses. However, LDC data cannot identify the ethnicity of directors. The first row of Figure A37 shows that the strongest effects occur in cheaper neighborhoods. Similarly, using IMD instead of the property price index, the second row of this figure shows that areas with lower IMD levels within the same postal district benefit most from platform expansion.

The previous analysis focused on within-district variation, showing that businesses tend to open in cheaper areas within districts. To understand the broader impact, I also examine the effects across entire postal districts, treating each district as a single unit. Figure A38 shows the impact is stronger in cheaper postal districts and also those with lower IMD. When combined with the earlier finding that FDAs increase the number of restaurants in both cheaper postal districts and cheaper quartiles within districts.

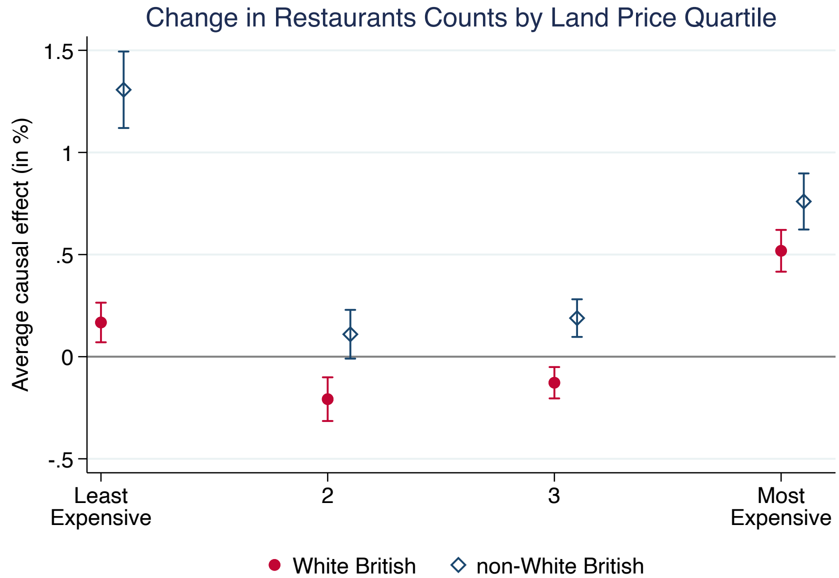


Figure 10. *Notes:* This figure illustrates the average causal effect of food delivery platform rollout on the demographics of entrepreneurs categorized as White British and non-White British, across different land price quartiles within postal districts. The x-axis represents land price quartiles, while the y-axis shows the average causal effect in percentage terms. The estimation is based on the specification in 19, 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.

5.4. **Impact on the Product Market: Enhancing Cuisine Diversity.** Does the democratization of restaurant entrepreneurship by the FDA influence the product market and affect consumers? In this section, I examine which cuisine types benefit most from FDAs and how this affects cuisine diversity and consumer options.

Entrepreneurs tend to offer cuisines that match their cultural backgrounds. This phenomenon, known as homophily, suggests that individuals prefer to engage with those who are similar to themselves. Minority entrepreneurs, in particular, may lean toward offering culturally familiar cuisines. If homophily holds, and FDAs disproportionately help underrepresented groups, the result could be a wider variety of cuisines available to consumers.

Descriptive evidence supports this homophily in the restaurant industry. Figure A39 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 group g, and $\mathbb{I}[i \in g]$ is a binary variable indicating whether the restaurant's cuisine corresponds to 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 FDA-partnered restaurants.

The results, shown in Figure 11, 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 the degree of homophily seems to be stronger for overall restaurants compared to those on food delivery platforms [16].

Given this homophily link, the democratization enabled by FDAs should have a downstream impact on the product market. I compare restaurants on FDAs 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 A31 panel (c) shows that non-UK cuisine types are more prevalent among FDA-affiliated establishments.

To measure the impact of FDAs on each cuisine type, I calculate percentage changes in the number of restaurants. However, equation 18 is specified in levels rather than logs due to the fact that in many period-geographical unit combinations, there are no restaurants of a particular cuisine. Consequently, percentage changes are reported by computing $\Delta\hat{y}_m = \hat{\beta_m}/E(y_m|D_{it} = 0)$, where $/E(y_m|D_{it} = 0)$ is the average number of restaurants of cuisine type m in regions before the arrival of food delivery platforms.

Figure 12 depicts these estimators, providing a visual representation of the impact across different cuisine types. Each point represents a coefficient estimated from a separate regression analysis similar to Equation 18. In these regressions, the outcome variable is the number of restaurants specializing in a specific cuisine type. For further details, Appendix Figure A40 illustrates the impact in levels.

The results show that the rise in specific cuisine-type restaurants (Figure 12) coincides with an increase in entrepreneurs from those regions (Figure 9). This supports the idea that 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.

A potential concern with the disproportionate benefit of food delivery platforms 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

[16] 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 platforms weaken the tie between location and clientele, allowing them to serve diverse audiences beyond their local ethnic communities.

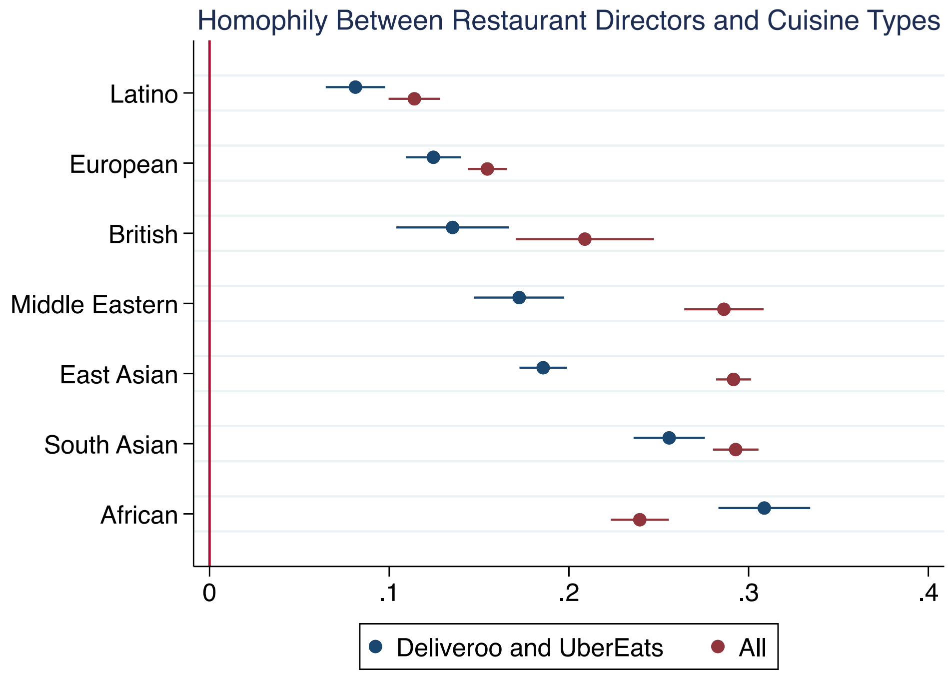


Figure 11. *Notes:* This figure illustrates the degree of homophily between restaurant directors and the cuisine type of their restaurant. Directors' backgrounds are inferred from their first and last names as described in the text, using data from Companies House. Restaurants listed in Companies House 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.

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 the restaurant cuisine types, we would expect to see a similar effect. However, as Figure A41 shows, there is no significant correlation between platform rollout and spending on these items.

Does this heterogeneous impact across cuisine types translate into greater overall diversity? To examine this, I analyze two diversity metrics. The first is the Herfindahl-Hirschman Index (HHI), calculated based on cuisine types, and the second is the number of distinct cuisine categories available. I define cuisine types at two levels of granularity—for example, one broad category like "Indian" and another more specific, such as "South Asian." Table 1 presents the results for both

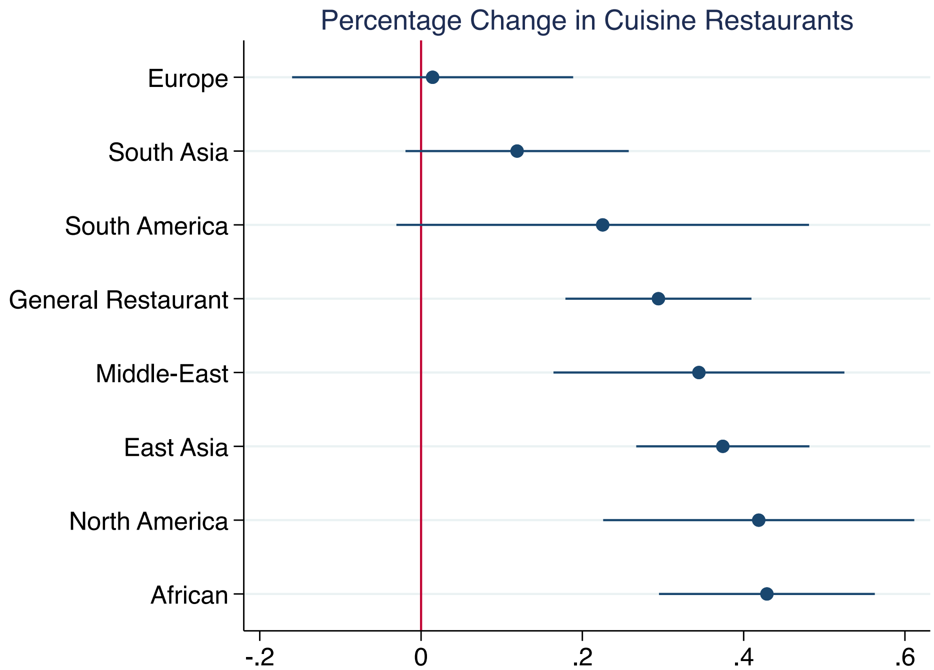


Figure 12. *Notes:* The figure shows the impact of the platform on different cuisine types, reported as the percentage changes by computing $\Delta\hat{y}_m = \hat{\beta_m}/E(\hat{y_m}|D_{it} = 1)$, where $E(\hat{y_m}|D_{it} = 1)$ is the average predicted number of cuisine m restaurants after the rollout 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.

categorization methods, showing that the rollout of food delivery platforms leads to an increase in cuisine diversity across all metrics.

6. Conclusion

The impact of food delivery applications on the restaurant industry exemplifies the broader business and employment structures offered by e-marketplaces, characterized by a shift toward lower entry barriers and deeper market integration. 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; in fact, migrant-owned restaurants on the apps have higher

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 platforms (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).

productivity than both migrant-owned restaurants not on the apps and non-migrant restaurants on the apps. Instead, as e-marketplaces reduce and standardize entry barriers, groups that face more challenges in traditional settings—like credit constraints—gain the most.

Two key mechanisms may help explain this democratizing effect. First, they reduce the need for physical space, which disproportionately benefits disadvantaged groups, such as those with limited access to capital. Second, in theory, platforms could help minority-owned restaurants reach a wider demographic, potentially allowing them to overcome barriers to penetrate majority-dominated neighborhoods or bypass face-to-face biases. However, the evidence suggests that the main advantage for minority entrepreneurs comes from lower fixed costs, rather than accessing new customer demographics.

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 platform 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 platforms. 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 much can we infer about other digital marketplaces from this setting? Restaurants, with their short life cycles and relatively unregulated spatial patterns, are highly sensitive to urban changes, making the industry an ideal lens to study the broader economic impact of digital platforms. To extend these insights, however, we need to think about how lowered entry barriers and market integration operate in other contexts. While reduced barriers to entry seem to be common across many 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 positive impact on the number of restaurants. In contrast, in digital marketplaces like Amazon or Google Play, competition is national or global, which can lead to dominance by a few large firms, limiting the benefits of lower entry barriers for smaller businesses.

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. By enhancing digital literacy and providing infrastructure support, policymakers can level the playing field, enabling a more diverse range of businesses to thrive. Effective policy interventions can thus harness the potential of digital platforms to drive inclusive economic growth and innovation in the food service sector.

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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.[17] 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

[17] 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 A42 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 platforms 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 Maximisation Problem.** In this section, I solve the utility maximization problem. The sub-utility function u_h is defined as:

$$u_h = \left(\int_{\Omega^h} \int_0^1 q_h(\omega, v)^{\frac{\sigma-1}{\sigma}} \, dv \, d\omega \right)^{\frac{\sigma}{\sigma-1}},$$

where:

- Ω^h is the set of all sector h firms,
- σ is the elasticity of substitution between varieties within the same sector,
- $q_h(\omega, v)$ is the quantity consumed of variety v, produced by firm ω in sector h.

The total expenditure on goods in sector h must equal the income allocated to that sector:

$$\int_{\Omega^h} \int_0^1 p_h(\omega, v) q_h(\omega, v) \, dv \, d\omega = \beta_h Y,$$

where:

- $p_h(\omega, v)$ is the price of variety v produced by firm ω in sector h,
- β_h is the expenditure share on sector h,
- Y is the total income (or expenditure).

We now formulate the Lagrangian function, which combines the utility function and the budget constraint, using λ as the Lagrange multiplier:

$$L = \left(\int_{\Omega^h} \int_0^1 q_h(\omega, v)^{\frac{\sigma-1}{\sigma}} \, dv \, d\omega \right)^{\frac{\sigma}{\sigma-1}} + \lambda \left(\beta_h Y - \int_{\Omega^h} \int_0^1 p_h(\omega, v) q_h(\omega, v) \, dv \, d\omega \right)$$

The first-order condition with respect to $q_h(\omega, v)$ is:

$$(q_h(\omega, v))^{\frac{-1}{\sigma}} \left(\int_{\Omega^h} \int_0^1 q_h(\omega, v)^{\frac{\sigma-1}{\sigma}} \, dv \, d\omega \right)^{\frac{1}{\sigma-1}} - \lambda p_h(\omega, v) = 0 \tag{20}$$

and the first-order condition with respect to λ is:

$$\int_{\Omega^h} \int_0^1 p_h(\omega, v) q_h(\omega, v) \, dv \, d\omega - \beta_h Y = 0 \tag{21}$$

Let us define Z as:

$$Z = \left(\int_{\Omega^h} \int_0^1 q_h(\omega, v)^{\frac{\sigma-1}{\sigma}} \, dv \, d\omega \right)$$

From equation 20, we can derive an expression for the quantity consumed of variety v:

$$q_h(\omega, v) = \frac{Z^{\frac{\sigma}{\sigma-1}}}{(\lambda p_h(\omega, v))^{\sigma}} \tag{22}$$

Substituting into equation 21, we have:

$$\int_{\Omega^h} \int_0^1 p_h(\omega, v) \frac{Z^{\frac{\sigma}{\sigma-1}}}{(\lambda p_h(\omega, v))^{\sigma}} \, dv \, d\omega = \beta_h Y$$

$$\lambda^{-\sigma} Z^{\frac{\sigma}{\sigma-1}} \int_{\Omega^h} \int_0^1 p_h(\omega, v)^{1-\sigma} \, dv \, d\omega = \beta_h Y$$

Now, the price index for firm ω is:

$$p^h(\omega) = \left[\int_0^1 p(\omega, v)^{1-\sigma} dv \right]^{1/(1-\sigma)}$$

Thus, we have:

$$\lambda^{-\sigma} Z^{\frac{\sigma}{\sigma-1}} \int_{\Omega^h} p_h(\omega, v)^{1-\sigma} \, d\omega = \beta_h Y$$

The aggregate price index for sector h is defined as follows:

$$P^h = \left[\int_{\Omega^h} p^h(\omega)^{1-\sigma} d\omega \right]^{1/(1-\sigma)}$$

Thus, we obtain:

$$\lambda^{-\sigma} Z^{\frac{\sigma}{\sigma-1}} P_h^{1-\sigma} = \beta_h Y$$

The Lagrange multiplier λ is then given by:

$$\lambda = \frac{Z^{\frac{1}{\sigma-1}} (P^h)^{\frac{1-\sigma}{\sigma}}}{(\beta_h Y)^{\frac{1}{\sigma}}} \tag{23}$$

Substituting the expression for λ from equation 23 into equation 22, we obtain:

$$q_h(\omega, v) = \beta_h Y P_h^{\sigma-1} p_h(\omega, v)^{-\sigma}$$

A5.2. **CDF of the Marginal Cost for Two-Channel Firms.** The CDF of the marginal cost c for a two-channel firm, $G^{h,TC}(c)$, is constructed by considering the minimum of the marginal costs associated with each channel, given the independent taste shocks following a Fréchet distribution. Here's a detailed explanation:

As said, for a two-channel firm, the marginal cost of delivering a product through each channel is given by:

$$\text{Online Channel} : \frac{w\tau^{h,E}}{\phi v^E}$$
$$\text{Offline Channel} : \frac{w\tau^{h,P}}{\phi v^P}$$

The firm will choose the channel with the lower marginal cost for each variety. Therefore, the effective marginal cost c is:

$$c = \min \left(\frac{w\tau^{h,E}}{\phi v^E}, \frac{w\tau^{h,P}}{\phi v^P} \right)$$

The taste shocks v^E and v^P are assumed to follow a Fréchet distribution with a shape parameter θ:

$$\Pr(v^m \leq x) = \exp(-x^{-\theta}) \quad \text{for} \quad m \in \{E, P\}$$

Since the taste shocks v^E and v^P are independent, the distribution of the marginal cost c involves combining the distributions of both channels. We know to find the CDF of the minimum of two independent random variables X and Y with CDFs $F_X(x)$ and $F_Y(y)$, respectively, we use:

$$\Pr(\min(X,Y) \leq c) = 1 - \Pr(\min(X,Y) > c) = 1 - \Pr(X > c)\Pr(Y > c)$$

Applying this to our problem:

$$G(c) = 1 - \Pr\left(\frac{w\tau^{h,E}}{\phi v^E} > c\right)\Pr\left(\frac{w\tau^{h,P}}{\phi v^P} > c\right)$$

We transform the inequalities to express them in terms of the taste shocks and use the CDF of the Fréchet distribution:

$$\Pr\left(\frac{w\tau^{h,E}}{\phi v^E} > c\right) = \Pr\left(v^E < \frac{w\tau^{h,E}}{\phi c}\right) = \exp\left(-\left(\frac{w\tau^{h,E}}{\phi c}\right)^{-\theta}\right)$$

$$\Pr\left(\frac{w\tau^{h,P}}{\phi v^P} > c\right) = \Pr\left(v^P < \frac{w\tau^{h,P}}{\phi c}\right) = \exp\left(-\left(\frac{w\tau^{h,P}}{\phi c}\right)^{-\theta}\right)$$

Now, we calculate the product of the probabilities:

$$\begin{aligned}&\Pr\left(\frac{w\tau^{h,E}}{\phi v^E} > c\right)\Pr\left(\frac{w\tau^{h,P}}{\phi v^P} > c\right)\\ &= \left[\exp\left(-\left(\frac{w\tau^{h,E}}{\phi c}\right)^{-\theta}\right)\right]\left[\exp\left(-\left(\frac{w\tau^{h,P}}{\phi c}\right)^{-\theta}\right)\right]\\ &= \exp\left(-\left(\left(\frac{w\tau^{h,E}}{\phi c}\right)^{-\theta} + \left(\frac{w\tau^{h,P}}{\phi c}\right)^{-\theta}\right)\right)\end{aligned}$$

Therefore, the CDF of the marginal cost c for the two-channel firm is:

$$\begin{aligned}G^{h,TC}(c) &= 1 - \exp\left(-\left(\left(\frac{w\tau^{h,E}}{\phi c}\right)^{-\theta} + \left(\frac{w\tau^{h,P}}{\phi c}\right)^{-\theta}\right)\right)\\ &= 1 - \exp\left(-\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta} c^{\theta}\right).\end{aligned}$$

A5.3. **Firm-Level Optimum Price Level.** The firm-level price index $p^h(\omega)$ for firm ω is:

$$p^h(\omega) = \left[\int_0^1 p^h(\omega, v)^{1-\sigma} dv\right]^{1/(1-\sigma)}.$$

With CES utility and monopolistic competition, the firm sets a price that is a constant markup over marginal cost:

$$p^h(\omega, v) = \frac{\sigma}{\sigma - 1} c(v).$$

Here we should deriving the firm-level price index for hybrid restaurants. The case for online-only restaurants would be easier. The firm-level price index $p^h(\omega)$ aggregates over all varieties produced by the firm:

$$
\begin{aligned}
p^{h,TC}(\phi) &= \left[\int_0^1 \left(\frac{\sigma}{\sigma-1}c(v)\right)^{1-\sigma} dv\right]^{1/(1-\sigma)}. \\
&= \frac{\sigma}{\sigma-1}\left[\int_0^1 c(v)^{1-\sigma} dv\right]^{1/(1-\sigma)}. \\
&= \frac{\sigma}{\sigma-1}\left[\int_0^\infty c^{1-\sigma} f_C(c)dc\right]^{1/(1-\sigma)}. \\
&= \frac{\sigma}{\sigma-1}\left[\int_0^\infty c^{1-\sigma} g^{h,TC}(c)dc\right]^{1/(1-\sigma)}.
\end{aligned}
$$

Here, $g^{h,TC}(c)$ is the probability density function associated with $G^{h,TC}(c)$. This function is equal to:

$$
g^{h,TC}(c) = \frac{d}{dc}G^{h,TC}(c) = \theta\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)c^{\theta-1}\exp\left(-\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)c^{\theta}\right)
$$

Substituting $g^{h,TC}(c)$:

$$
\begin{aligned}
\int_0^\infty c^{1-\sigma}g^{h,TC}(c)dc &= \int_0^\infty c^{1-\sigma}\theta\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)c^{\theta-1}\exp\left(-\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)c^{\theta}\right)dc \\
&= \theta\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)\int_0^\infty c^{\theta-\sigma}\exp\left(-\left(\sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)c^{\theta}\right)dc
\end{aligned}
$$

This integral matches the form of a known integral involving the Fréchet distribution. Specifically, it is of the form:

$$
\int_0^\infty x^a \exp(-bx^c)\,dx = \frac{1}{b^{\frac{a+1}{c}}c}\Gamma\left(\frac{a+1}{c}\right)
$$

where $a = \theta - \sigma$, $b = \sum_{m\in\{E,P\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}$, and $c = \theta$.

This will lead to:

$$
\int_0^\infty c^{1-\sigma}g^{h,TC}(c)dc = \left(\sum_{m\in\{P,E\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)^{\frac{1-\sigma}{\theta}}\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)
$$

Thus, the firm-level price index becomes:

$$
p^{h,TC}(\phi) = \frac{\sigma}{\sigma-1}\left(\mathbb{E}[c^{1-\sigma}]\right)^{1/(1-\sigma)} = \frac{\sigma}{\sigma-1}\left(\left(\sum_{m\in\{P,E\}}\left(\frac{w\tau^{h,m}}{\phi}\right)^{-\theta}\right)^{\frac{1-\sigma}{\theta}}\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right)^{1/(1-\sigma)}
$$

Finally, simplifying and combining constants gives us:

$$p^{h,TC}(\phi) = \frac{\kappa^{\frac{1}{1-\sigma}} w}{\phi} \left(\sum_{m \in \{P,E\}} \left(\tau^{h,m}\right)^{-\theta} \right)^{-\frac{1}{\theta}}$$

where $\kappa = \Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}$.

A5.4. **Proportion of Online Sales.** The proportion of sales via the online channel, ρ, is derived based on the distribution of marginal costs and the resulting choice of sales channels by the firm. We know that the taste shocks for the online channel (v^E) and the offline channel (v^P) are drawn from a Fréchet distribution with the CDF $\Pr(v^m \leq x) = \exp(-x^{-\theta})$. Also, the marginal cost of delivering one quality unit to consumers is $c^E = \frac{w\tau^{h,E}}{\phi v^E}$ for online channel and is $c^P = \frac{w\tau^{h,P}}{\phi v^P}$ for the offline channel.

For each variety, the firm chooses the channel that offers the lower unit cost of production and delivery. The expected cost for each channel, i.e., online channel, given the Fréchet distribution, we need to calculate the probability that the online channel offers a lower marginal cost than the offline channel. This can be derived from the distribution of the taste shocks.

We can write the probability that $c^E \leq c^P$ as:

$$\Pr\left(c^E \leq c^P\right) = \Pr\left(\frac{w\tau^{h,E}}{\phi v^E} \leq \frac{w\tau^{h,P}}{\phi v^P}\right)$$

Since the w and ϕ terms cancel out, we are left with:

$$\Pr\left(\frac{\tau^{h,E}}{v^E} \leq \frac{\tau^{h,P}}{v^P}\right) = \Pr\left(v^P \leq kv^E\right)$$

where $k = \frac{\tau^{h,P}}{\tau^{h,E}}$. The probability $\Pr(v^P \leq kv^E)$ is given by:

$$\Pr(v^P \leq kv^E) = \int_0^\infty \Pr(v^P \leq ky) f_{v^E}(y)\, dy$$

Since v^P and v^E are identically distributed:

$$\Pr(v^P \leq ky) = \exp(-k^{-\theta} y^{-\theta})$$

Therefore:

$$\Pr(v^P \leq kv^E) = \int_0^\infty \exp(-k^{-\theta} y^{-\theta}) f_{v^E}(y)\, dy$$

Substitute the PDF of v^E:

$$f_{v^E}(y) = \frac{\theta}{y^{\theta+1}} \exp(-y^{-\theta})$$

The integral becomes:

$$\begin{aligned}\Pr(v^P \leq kv^E) &= \int_0^\infty \exp(-k^{-\theta} y^{-\theta}) \frac{\theta}{y^{\theta+1}} \exp(-y^{-\theta})\, dy \\ &= \int_0^\infty \frac{\theta}{y^{\theta+1}} \exp(-y^{-\theta}(1 + k^{-\theta}))\, dy\end{aligned}$$

To solve this integral, make a substitution $u = y^{-\theta}$, hence $du = -\theta y^{-\theta-1}dy$:

$$\int_0^\infty \frac{\theta}{y^{\theta+1}} \exp(-y^{-\theta}(1+k^{-\theta}))\, dy = \int_0^\infty \exp(-u(1+k^{-\theta}))\, du$$

$$= \int_0^\infty \exp(-u(1+k^{-\theta}))\, du = \frac{1}{1+k^{-\theta}}$$

Thus, the probability is:

$$\Pr\left(\frac{\tau^{h,E}}{v^E} \leq \frac{\tau^{h,P}}{v^P}\right) = \frac{1}{1+k^{-\theta}}$$

Substitute $k = \frac{\tau^{h,P}}{\tau^{h,E}}$:

$$\Pr\left(\frac{\tau^{h,E}}{v^E} \leq \frac{\tau^{h,P}}{v^P}\right) = \frac{1}{1+\left(\frac{\tau^{h,P}}{\tau^{h,E}}\right)^{-\theta}}$$

We can derive:

$$\rho = \Pr\left(\frac{\tau^{h,E}}{v^E} \leq \frac{\tau^{h,P}}{v^P}\right) = \frac{(\tau^{h,E})^{-\theta}}{(\tau^{h,E})^{-\theta} + (\tau^{h,P})^{-\theta}} = \frac{(\tau^{h,E})^{-\theta}}{\sum_{m\in\{P,E\}}(\tau^{h,m})^{-\theta}}$$

A5.5. **Productivity Cutoff.** This subsection provides a detailed step-by-step derivation of the productivity cutoff equation for a firm deciding whether to set up a physical store or operate only through the online channel. A firm will set up a physical store if the profit from being a two-channel firm exceeds the profit from being an online-only firm:

$$\pi^{h,TC}(\phi) > \pi^{h,ON}(\phi)$$

$$\frac{1}{\sigma}s^{h,TC}(\phi) - wf^P > \frac{1}{\sigma}s^{h,ON}(\phi)$$

$$s^{h,TC}(\phi) - s^{h,ON}(\phi) > \sigma w f^P$$

Substitute the expressions for $s^{h,TC}(\phi)$ and $s^{h,ON}$, and factoring out common terms:

$$\frac{\kappa\beta^h Y w^{1-\sigma}}{(P^h)^{1-\sigma}}\phi^{\sigma-1}\left[\left(\sum_{m\in\{P,E\}}(\tau^{h,m})^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - (\tau^{h,E})^{1-\sigma}\right] > \sigma w f^P$$

We can isolate $\phi^{\sigma-1}$ as:

$$\phi^{\sigma-1} > \frac{\sigma w f^P (P^h)^{1-\sigma}}{\kappa\beta^h Y w^{1-\sigma}\left[\left(\sum_{m\in\{P,E\}}(\tau^{h,m})^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - (\tau^{h,E})^{1-\sigma}\right]}$$

$$\phi^{\sigma-1} > \frac{\sigma w f^P}{\kappa\beta^h Y}(\frac{P^h}{w})^{1-\sigma}\left[\left(\sum_{m\in\{P,E\}}(\tau^{h,m})^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^{h,E})^{1-\sigma}\right]^{-1}$$

Take the $(\sigma-1)$-th root on both sides to solve for ϕ:

$$\phi > \left(\frac{\sigma w f^P}{\kappa \beta^h Y}\right)^{\frac{1}{\sigma-1}} (\frac{P^h}{w})^{-1} \left[\left(\sum_{m \in \{P,E\}} (\tau^{h,m})^{-\theta} \right)^{\frac{\sigma-1}{\theta}} - (\tau^{h,E})^{1-\sigma} \right]^{\frac{1}{\sigma-1}}$$

The final necessary and sufficient condition for a firm to set up a physical store, expressed as a productivity cutoff ϕ^* is:

$$\phi^* = \left(\frac{\kappa \beta^h Y}{\sigma w f^P}\right)^{\frac{1}{1-\sigma}} \frac{w}{P^h} \left[\left(\sum_{m \in \{P,E\}} \left(\tau^{h,m}\right)^{-\theta} \right)^{\frac{\sigma-1}{\theta}} - \left(\tau^{h,E}\right)^{1-\sigma} \right]^{\frac{1}{\sigma-1}}$$

A5.6. **E-commerce Switch Cutoff.** This section demonstrates how the free entry condition can be used to determine the cutoff that dictates which firms will opt for e-commerce and which will choose a hybrid model. The free entry condition, as expressed in equation 11, can be written as:

$$\int_{\underline{\phi}}^{\phi^*} \pi^{ON}(\phi) dF(\phi) + \int_{\phi^*}^{\infty} \pi^{TC}(\phi) dF(\phi) = w \cdot F_{\text{entry}}$$

Setting w as the numeraire and imputing values for productivity, we can write the free entry condition as:

$$\begin{aligned}
&\int_{\underline{\phi}}^{\phi^*} \frac{1}{\sigma} \kappa \beta^h Y P^{\sigma-1} \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1} dF(\phi) \\
&+ \int_{\phi^*}^{\infty} \left(\frac{1}{\sigma} \kappa \beta^h Y P^{\sigma-1} \left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta} \right)^{-\frac{1-\sigma}{\theta}} \phi^{\sigma-1} - f^P \right) dF(\phi) \\
&= F_{\text{entry}}
\end{aligned}$$

To simplify the free entry condition, we first define:

$$B_p = \frac{1}{\sigma} \kappa \beta^h Y P^{\sigma-1}.$$

This allows us to rewrite the free entry condition as:

$$\begin{aligned}
&\int_{\underline{\phi}}^{\phi^*} B_p \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1} dF(\phi) \\
&+ \int_{\phi^*}^{\infty} \left(B_p \left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta} \right)^{-\frac{1-\sigma}{\theta}} \phi^{\sigma-1} - f^P \right) dF(\phi) \\
&= F_{\text{entry}}.
\end{aligned}$$

We can insert the definition of B_p in equation 10, the productivity cutoff ϕ^*, to get:

$$\phi^* = \left(\frac{B_p}{f^P}\right)^{\frac{1}{1-\sigma}} \left[\left(\sum_{m \in \{P,E\}} (\tau^m)^{-\theta} \right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}.$$

Then:

$$B_p = \frac{f^P}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \phi^{*(1-\sigma)}.$$

Substituting B_p, the free entry condition becomes:

$$\begin{aligned}
&\int_{\underline{\phi}}^{\phi^*} \frac{\left(\tau^E\right)^{1-\sigma}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \left(\frac{\phi}{\phi^*}\right)^{\sigma-1} dF(\phi) \\
&+ \int_{\phi^*}^{\infty} \frac{\left((\tau^P)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \left(\frac{\phi}{\phi^*}\right)^{\sigma-1} dF(\phi) - \int_{\phi^*}^{\infty} dF(\phi) \\
&= \frac{F_{\text{entry}}}{f^P}.
\end{aligned}$$

Now we evaluate the integrals. Given that the CDF for ϕ follows a Pareto distribution:

$$F(\phi) = 1 - \left(\frac{\underline{\phi}}{\phi}\right)^{\alpha},$$

the PDF is:

$$f(\phi) = \frac{d}{d\phi} F(\phi) = \alpha \frac{\underline{\phi}^{\alpha}}{\phi^{\alpha+1}}, \quad \phi \geq \underline{\phi}.$$

First Integral: substituting the PDF into the first integral:

$$\begin{aligned}
&\int_{\underline{\phi}}^{\phi^*} \left(\frac{\phi}{\phi^*}\right)^{\sigma-1} \alpha \frac{\underline{\phi}^{\alpha}}{\phi^{\alpha+1}} d\phi \\
&= \frac{\alpha \underline{\phi}^{\alpha}}{(\phi^*)^{\sigma-1}} \int_{\underline{\phi}}^{\phi^*} \phi^{\sigma-\alpha-2} d\phi \\
&= \frac{\alpha}{1+\alpha-\sigma} \left[\left(\frac{\underline{\phi}}{\phi^*}\right)^{\sigma-1} - \left(\frac{\underline{\phi}}{\phi^*}\right)^{\alpha} \right].
\end{aligned}$$

Second Integral

$$\int_{\phi^*}^{\infty} \left(\frac{\phi}{\phi^*}\right)^{\sigma-1} \alpha \frac{\phi^\alpha}{\phi^{\alpha+1}} d\phi$$
$$= \frac{\alpha}{1+\alpha-\sigma} \left(\frac{\phi}{\phi^*}\right)^{\alpha}.$$

Third Integral

$$\int_{\phi^*}^{\infty} dF(\phi) = 1 - F(\phi^*)$$
$$= \left(\frac{\phi}{\phi^*}\right)^{\alpha}.$$

Combining the results of these integrals, the free entry condition becomes:

$$\frac{\left(\tau^E\right)^{1-\sigma}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \frac{\alpha}{1+\alpha-\sigma} \left[\left(\frac{\phi}{\phi^*}\right)^{\sigma-1} - \left(\frac{\phi}{\phi^*}\right)^{\alpha}\right]$$
$$+ \frac{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \frac{\alpha}{1+\alpha-\sigma} \left(\frac{\phi}{\phi^*}\right)^{\alpha}$$
$$- \left(\frac{\phi}{\phi^*}\right)^{\alpha}$$
$$= \frac{F_{\text{entry}}}{f^P}.$$

To simplify, we first combine the terms that involve $\left(\frac{\phi}{\phi^*}\right)^{\alpha}$. This gives us:

$$\left(\frac{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma} - \frac{\left(\tau^E\right)^{1-\sigma}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - (\tau^E)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma} - 1\right) \left(\frac{\phi}{\phi^*}\right)^{\alpha}.$$

$$\left(\frac{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma}}{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma} - 1\right) \left(\frac{\phi}{\phi^*}\right)^{\alpha} = \left(\frac{\sigma-1}{1+\alpha-\sigma}\right) \left(\frac{\phi}{\phi^*}\right)^{\alpha}$$

Thus, the equation can be rewritten as:

$$\left(\frac{\sigma-1}{1+\alpha-\sigma}\right) \left(\frac{\phi}{\phi^*}\right)^{\alpha} + \left(\frac{\left(\tau^E\right)^{1-\sigma}}{\left((\tau^P)^{-\theta} + (\tau^E)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma}\right) \left(\frac{\phi}{\phi^*}\right)^{\sigma-1} = \frac{F_{\text{entry}}}{f^P}.$$

A5.7. **Price Index Decomposition.** This section goes through the algebraic derivation step by step to break down the change in the price index $((P^T)^{1-\sigma}$ into four components A, B, C, and D.

$$
\begin{aligned}
\Delta(P^T)^{1-\sigma} &= (P^{T'})^{1-\sigma} - (P^T)^{1-\sigma} \\
&= M^{T'}\left(\int_{\underline{\phi}}^{\phi^{*'}} (p^{ON'}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*'}}^{\infty} (p^{TC'}(\phi))^{1-\sigma} dF(\phi)\right) \\
&\quad - M^{T}\left(\int_{\underline{\phi}}^{\phi^{*}} (p^{ON}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*}}^{\infty} (p^{TC}(\phi))^{1-\sigma} dF(\phi)\right)
\end{aligned}
$$

Add and subtract the term with the same mass of firms:

$$
\begin{aligned}
\Delta(P^T)^{1-\sigma} &= M^{T'}\left(\int_{\underline{\phi}}^{\phi^{*'}} (p^{ON'}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*'}}^{\infty} (p^{TC'}(\phi))^{1-\sigma} dF(\phi)\right) \\
&- M^{T}\left(\int_{\underline{\phi}}^{\phi^{*}} (p^{ON}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*}}^{\infty} (p^{TC}(\phi))^{1-\sigma} dF(\phi)\right) \\
&+ M^{T}\left(\int_{\underline{\phi}}^{\phi^{*'}} (p^{ON'}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*'}}^{\infty} (p^{TC'}(\phi))^{1-\sigma} dF(\phi)\right) \\
&- M^{T}\left(\int_{\underline{\phi}}^{\phi^{*'}} (p^{ON'}(\phi))^{1-\sigma} dF(\phi) + \int_{\phi^{*'}}^{\infty} (p^{TC'}(\phi))^{1-\sigma} dF(\phi)\right)
\end{aligned}
$$

Combining terms involving $M^{T'}$ and M^T:

$$
\begin{aligned}
\Delta(P^T)^{1-\sigma} = M^{T}&\left(\int_{\underline{\phi}}^{\phi^{*}} \left(p^{ON'}(\phi)\right)^{1-\sigma} - \left(p^{ON}(\phi)\right)^{1-\sigma} dF(\phi) + \int_{\phi^{*}}^{\phi^{*'}} (p^{ON'}(\phi))^{1-\sigma} dF(\phi)\right) \\
+ M^{T}&\left(\int_{\underline{\phi}}^{\phi^{*}} \left(p^{TC'}(\phi)\right)^{1-\sigma} - \left(p^{TC}(\phi)\right)^{1-\sigma} dF(\phi) + \int_{\phi^{*}}^{\phi^{*'}} (p^{TC'}(\phi))^{1-\sigma} dF(\phi)\right) \\
+ &\left(M^{T'} - M^{T}\right)\overline{\Psi}'
\end{aligned}
$$

We then get:

$$
\begin{aligned}
\Delta\left(P^T\right)^{1-\sigma} =& M^{T}\left(\int_{\phi}^{\phi^{*}} \left(p^{ON'}(\phi)\right)^{1-\sigma} - \left(p^{ON}(\phi)\right)^{1-\sigma} dF(\phi)\right) \\
&+ M^{T}\left(\int_{\phi^{*}}^{\infty} \left(p^{TC'}(\phi)\right)^{1-\sigma} - \left(p^{TC}(\phi)\right)^{1-\sigma} dF(\phi)\right) \\
&+ \left(M^{T'} - M^{T}\right)\overline{\Psi} \\
&+ M^{T}\left(\int_{\phi^{*}}^{\phi^{*'}} \left(p^{ON'}(\phi)\right)^{1-\sigma} - \left(p^{TC'}(\phi)\right)^{1-\sigma} dF(\phi)\right) + \left(M^{T'} - M^{T}\right)\left(\overline{\Psi}' - \overline{\Psi}\right)
\end{aligned}
\tag{24}
$$

A5.8. **Real Wage inversely related to Welfare.** In this subsection, I show the welfare of a representative worker being given by W/P in the context of the Melitz (2003) model is rooted in the CES (Constant Elasticity of Substitution) preferences of the representative agent. Here, I will show the detailed reasoning and mathematical proof.

The price index is given by:

$$P^h = \left[\int_{\Omega^h} \int_0^1 p^h(\omega, v)^{1-\sigma} dv d\omega \right]^{1/(1-\sigma)}. \tag{25}$$

Utility is given by:

$$u^h = \left(\int_{\Omega^h} \int_0^1 q^h(\omega, v)^{(\sigma-1)/\sigma} dv d\omega \right)^{\sigma/(\sigma-1)},$$

We already showed:

$$q^h(\omega, v) = \beta^h \frac{Y p^h(\omega, v)^{-\sigma}}{(P^h)^{1-\sigma}}, \tag{26}$$

Substituting this we will have:

$$u^h = \beta^h Y P^{\sigma-1} \left[\int_{\Omega^h} \int_0^1 p^h(\omega, v)^{1-\sigma} dv d\omega \right]^{\sigma/(\sigma-1)} = \frac{\beta^h Y}{P}$$

A5.9. **Proof of the Impact of E-commerce.** **Proof of (a):** After the e-commerce firms have access to online mode. The profit function for an online-only firm, given by $\frac{1}{\sigma}\kappa\beta_h Y w^{1-\sigma} P^{\sigma-1} \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1}$, is strictly positive for all $\phi > 0$. Therefore, no firm will exit the market under this condition.

Proof of (b): Initially, when $\tau^E \to \infty$ (i.e., in the absence of e-commerce), the productivity cutoff is $\phi^* = \phi^a$, indicating the threshold for operating offline. As τ^E decreases (representing the increasing availability and lowering cost of e-commerce), ϕ^* rises, since $\frac{\partial \phi^*}{\partial \tau^E} < 0$ (already shown). This implies that as e-commerce becomes more accessible, the productivity cutoff for hybrid firms increases, i.e., $\phi^* > \phi^a$

Firms with productivity ϕ such that $\phi^a \leq \phi < \phi^*$ were previously operating physical stores because their productivity was sufficient to cover the fixed cost wf^P. However, with the introduction of e-commerce, these firms now face a higher cutoff ϕ^* to operate physical stores profitably.

Proof of (c):

Before the advent of e-commerce, the mass of active firms M_1 can be expressed as:

$$M_1 = \frac{R}{\bar{r}} = \frac{L}{\sigma(\bar{\pi} + f)} = \frac{L}{\sigma \left(\frac{f_E}{1-G(\varphi^a)} + f_p \right)},$$

where we have used $\pi(\varphi) = \frac{r(\varphi)}{\sigma} - f$ and free entry condition.

After the introduction of e-commerce, the mass of active firms M_2 is given by:

$$M_2 = \frac{R}{\bar{r}}.$$

Given that a firm has a probability $P_o = G(\phi^*)$ of operating solely online and a probability $1-P_o$ of adopting a hybrid model, the average revenue $\bar{r}$ can be written as:

$$\begin{aligned}\bar{r} &= P_o\bar{r}_{ON} + (1-P_o)\bar{r}_{HF} = P_o\sigma\bar{\pi}_{ON} + (1-P_o)\sigma(\bar{\pi}_{HF} + f_P)\\ &= \sigma\left[P_o\bar{\pi}_0 + (1-P_o)\bar{\pi}_{HF} + (1-P_o)f_P\right] = \sigma\left[\bar{\pi} + (1-P_o)f_P\right]\end{aligned}$$

Substituting $\bar{r}$ into the expression for M_2, we have:

$$M_2 = \frac{R}{\bar{r}} = \frac{L}{\sigma\left[\bar{\pi} + (1-P_o)f_P\right]} = \frac{L}{\sigma\left[f_E + (1-P_o)f_p\right]}.$$

Here, we use the condition that after the adoption of e-commerce, the free entry condition implies $\bar{\pi} = f_E$.

Comparing M_1 and M_2, we see that M_2 is larger because its denominator is smaller. This comparison focuses on the mass of active firms. To further investigate, we now turn to a comparison of the mass of entrant firms. Post-e-commerce, the mass of entrants is identical to the mass of active firms. However, prior to the adoption of e-commerce, the mass of entrants can be expressed as:

$$M_{1,E} = \frac{M_1}{1-G(\phi^a)} = \frac{L}{\sigma\left[f_E + (1-G(\phi^a))f_p\right]}.$$

Given that $\phi^* > \phi^a$ implies $P_o = G(\phi^*) > G(\phi^a)$, it follows that $M_{2,E} = M_2 > M_{1,E}$.

Proof of (d):

A5.10. **Proof of Comparative Statics.** **Proof of (a):**

Starting from the free entry condition given by Equation 12, we have:

$$\left[\frac{\sigma-1}{1+\alpha-\sigma}\right]\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \left[\frac{\left(\tau^E\right)^{1-\sigma}}{\left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{\frac{\sigma-1}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma}\right]\left(\frac{\phi}{\phi^*}\right)^{\sigma-1} = \frac{F_{\text{entry}}}{f^P}.$$

Setting $\tau^P = 1$ for simplicity:

$$\left[\frac{\sigma-1}{1+\alpha-\sigma}\right]\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \left[\frac{\left(\tau^E\right)^{1-\sigma}}{\left(1 + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma}\right]\left(\frac{\phi}{\phi^*}\right)^{\sigma-1} = \frac{F_{\text{entry}}}{f^P}.$$

Defining:

$$\Delta_1 = \frac{\sigma-1}{1+\alpha-\sigma},$$

$$\Delta_2 = \frac{\left(\tau^E\right)^{1-\sigma}}{\left(1 + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - \left(\tau^E\right)^{1-\sigma}} \cdot \frac{\alpha}{1+\alpha-\sigma}.$$

The equation becomes:

$$\Delta_1\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \Delta_2\left(\frac{\phi}{\phi^*}\right)^{\sigma-1} = \frac{F_{\text{entry}}}{f^P}.$$

To determine $\frac{\partial \phi^*}{\partial \tau^E}$, we differentiate both sides of the equation with respect to τ^E and apply the product rule:

$$\frac{\partial \Delta_1}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \Delta_1 \cdot \alpha \left(\frac{\phi}{\phi^*}\right)^{\alpha-1} \cdot \left(-\frac{\phi}{(\phi^*)^2}\right)\frac{\partial \phi^*}{\partial \tau^E}$$
$$+\frac{\partial \Delta_2}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\sigma-1} + \Delta_2 \cdot (\sigma-1)\left(\frac{\phi}{\phi^*}\right)^{\sigma-2} \cdot \left(-\frac{\phi}{(\phi^*)^2}\right)\frac{\partial \phi^*}{\partial \tau^E} = 0.$$

Isolating the terms involving $\frac{\partial \phi^*}{\partial \tau^E}$:

$$\frac{\partial \Delta_1}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \frac{\partial \Delta_2}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\sigma-1}$$
$$= -\left[\Delta_1 \cdot \alpha \left(\frac{\phi}{\phi^*}\right)^{\alpha-1} + \Delta_2 \cdot (\sigma-1)\left(\frac{\phi}{\phi^*}\right)^{\sigma-2}\right] \cdot \left(-\frac{\phi}{(\phi^*)^2}\right)\frac{\partial \phi^*}{\partial \tau^E}.$$

Now, solve for $\frac{\partial \phi^*}{\partial \tau^E}$:

$$\frac{\partial \phi^*}{\partial \tau^E} = \frac{\frac{\partial \Delta_1}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\alpha} + \frac{\partial \Delta_2}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\sigma-1}}{\left[\Delta_1 \cdot \alpha \left(\frac{\phi}{\phi^*}\right)^{\alpha-1} + \Delta_2 \cdot (\sigma-1)\left(\frac{\phi}{\phi^*}\right)^{\sigma-2}\right]} \cdot \frac{(\phi^*)^2}{\phi}.$$

Since Δ_1 is independent of τ^E, $\frac{\partial \Delta_1}{\partial \tau^E} = 0$, leaving:

$$\frac{\partial \phi^*}{\partial \tau^E} = \frac{\frac{\partial \Delta_2}{\partial \tau^E}\left(\frac{\phi}{\phi^*}\right)^{\sigma-1}}{\left[\Delta_1 \cdot \alpha \left(\frac{\phi}{\phi^*}\right)^{\alpha-1} + \Delta_2 \cdot (\sigma-1)\left(\frac{\phi}{\phi^*}\right)^{\sigma-2}\right]} \cdot \frac{(\phi^*)^2}{\phi}. \tag{27}$$

Given that all terms in the denominator are positive, the sign of $\frac{\partial \phi^*}{\partial \tau^E}$ depends on the sign of $\frac{\partial \Delta_2}{\partial \tau^E}$.

Lemma a1: $\frac{\partial \Delta_2(\tau^E)}{\partial \tau^E} < 0$

Differentiating $\Delta_2(\tau^E)$ with respect to τ^E yields:

$$\frac{\partial \Delta_2(\tau^E)}{\partial \tau^E} = \frac{\alpha}{1+\alpha-\sigma} \cdot$$
$$\frac{(1-\sigma)\left(\tau^E\right)^{-\sigma}\left[\left(1+\left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - \left(\tau^E\right)^{1-\sigma}\right] - \left(\tau^E\right)^{1-\sigma} \cdot (\sigma-1)\left[\left(\tau^E\right)^{-\sigma} - \left(\tau^E\right)^{-\theta-1}\left(1+\left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}-1}\right]}{\left[\left(1+\left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} - \left(\tau^E\right)^{1-\sigma}\right]^2}$$

Since all terms in the denominator are positive, and the factor $\frac{\alpha}{1+\alpha-\sigma}$ is also positive, the sign of this derivative hinges on the sign of the numerator. The numerator is negative for the following reasons:

- The first term in the numerator is negative because $1-\sigma < 0$ and other terms are positive.
- The second term in the numerator is positive. This follows because $\sigma < \theta + 1$ and $\tau^E > 1$ imply $\left(\tau^E\right)^{-\sigma} > \left(\tau^E\right)^{-\theta-1}$. Additionally, since $\left(1+\left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} < 1$, we have $\left(\tau^E\right)^{-\sigma} >$

$\left(\tau^E\right)^{-\theta-1}\left(1+\left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}-1}$, making the expression inside the bracket positive. Other terms are also positive.

Combining these observations, the numerator of $\frac{\partial \Delta_2(\tau^E)}{\partial \tau^E}$ is negative, leading to the conclusion that $\frac{\partial \Delta_2(\tau^E)}{\partial \tau^E}$ is negative.

With this lemma, we can conclude $\frac{\partial \phi^*}{\partial \tau^E} < 0$, confirming that as τ^E decreases, the proportion of restaurants opting for online sales increases.

Proof of (b):

We need to calculate $\frac{\partial M^h}{\partial \tau^E}$. Assuming a single sector with inelastic labour supply (?) and setting wage a numeraire to 1, from equation 14 we will have:

$$\begin{aligned}1 =& \frac{\sigma-1}{\sigma} M^h \left[\int_{\underline{\phi}}^{\phi^*} s^{ON}(\phi)\, dF(\phi) + \int_{\phi^*}^{\infty} s^{TC}(\phi)\, dF(\phi)\right] \\ &+ f^P M^h \left(1 - F\left(\phi^*\right)\right) + M^h F_{\text{Entry}}.\end{aligned}$$

Substituting for the s^{ON} and s^{TC}, we will get:

$$\begin{aligned}1 =& \frac{\sigma-1}{\sigma} M^h \left[\int_{\underline{\phi}}^{\phi^*} \kappa\beta^h Y P^{\sigma-1} \left(\tau^E\right)^{1-\sigma} \phi^{\sigma-1} dF(\phi)\right. \\ &\left. + \int_{\phi^*}^{\infty} \kappa\beta^h Y P^{\sigma-1} \left(\left(\tau^P\right)^{-\theta} + \left(\tau^E\right)^{-\theta}\right)^{-\frac{1-\sigma}{\theta}} \phi^{\sigma-1} dF(\phi)\right] \\ &+ f^P M^h \left(1 - F\left(\phi^*\right)\right) + M^h F_{\text{Entry}}.\end{aligned}$$

Let us define:

$$\begin{aligned}\Psi_1 &= \int_{\underline{\phi}}^{\phi^*} \alpha\kappa\beta^h Y w^{-\sigma} \tau_E^{1-\sigma} \underline{\phi}^{\alpha} \phi^{\sigma-\alpha-2} d\phi \\ \Psi_2 &= \int_{\phi^*}^{\infty} \alpha\kappa\beta^h Y w^{-\sigma} (\tau_P^{-\theta} + \tau_E^{-\theta})^{\frac{\sigma-1}{\theta}} \underline{\phi}^{\alpha} \phi^{\sigma-\alpha-2} d\phi \\ \Psi_3 &= \int_{\phi^*}^{\infty} \alpha \underline{\phi}^{\alpha} \phi^{-\alpha-1} d\phi\end{aligned}$$

Then, the labor market clearing condition can be written as:

$$1 = \frac{\sigma-1}{\sigma} M_R (P^{\sigma-1}\Psi_1 + P^{\sigma-1}\Psi_2) + f^P M_R \Psi_3 + M_R F_{entry}$$

This can be factored as:

$$M_R \left[\frac{\sigma-1}{\sigma}\left(P^{\sigma-1}\Psi_1 + P^{\sigma-1}\Psi_2\right) + f^P \Psi_3 + F_{entry}\right] = 1$$

Solving for M_R, we obtain:

$$M_R = \left[\frac{\sigma-1}{\sigma}\left(P^{\sigma-1}\Psi_1 + P^{\sigma-1}\Psi_2\right) + f^P\Psi_3 + F_{entry}\right]^{-1}$$

Next, recall from equation 2 (sector price index):

$$P^{1-\sigma} = M^T\left(\int_{\underline{\phi}}^{\phi^*}\left(p^{ON}(\phi)\right)^{1-\sigma}dF(\phi) + \int_{\phi^*}^{\infty}\left(p^{TC}(\phi)\right)^{1-\sigma}dF(\phi)\right)$$

Thus

$$P^{\sigma-1} = \frac{1}{M_R\left(\Gamma_1+\Gamma_2\right)}$$

where:

$$\Gamma_1 = \alpha\kappa w^{1-\sigma}\tau_E^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{\sigma-\alpha-1}\left[\phi_*^{\sigma-\alpha-1} - \underline{\phi}^{\sigma-\alpha-1}\right]$$

$$\Gamma_2 = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}\phi_*^{\sigma-\alpha-1}$$

This gives us:

$$M_R = \left[\frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{M_R\Gamma_1+M_R\Gamma_2} + f^P\Psi_3 + F_{entry}\right]^{-1}$$

Taking the reciprocal of both sides, we get:

$$M_R^{-1} = \frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{M_R\Gamma_1+M_R\Gamma_2} + f^P\Psi_3 + F_{entry}$$

Multiplying both sides by M_R:

$$1 = \frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2} + M_R\left(f^P\Psi_3 + F_{entry}\right)$$

Finally, solving for M_R again:

$$M_R = \frac{1-\frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2}}{f^P\Psi_3+F_{entry}}$$

Differentiating both sides of this equation with respect to τ_E:

$$\frac{\partial M_R}{\partial\tau_E} = \frac{\left(\frac{1-\sigma}{\sigma}\frac{\left(\frac{\partial\Psi_1}{\partial\tau_E}+\frac{\partial\Psi_2}{\partial\tau_E}\right)*(\Gamma_1+\Gamma_2)-\left(\frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\partial\Gamma_2}{\partial\tau_E}\right)*(\Psi_1+\Psi_2)}{(\Gamma_1+\Gamma_2)^2}\right)*\left(f^P\Psi_3+F_{entry}\right)-\left(f^P\frac{\partial\Psi_3}{\partial\tau_E}\right)*\left(1-\frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2}\right)}{(f^P\Psi_3+F_{entry})^2}$$

Lemma b1: $\Psi_3 > 0$ and $\frac{\partial\Psi_3}{\partial\tau_E} > 0$.

$$\Psi_3 = \underline{\phi}^{\alpha}\phi_*^{-\alpha} > 0$$

$$\frac{\partial\Psi_3}{\partial\tau_E} = \frac{\partial\Psi_3}{\partial\phi_*}*\frac{\partial\phi_*}{\partial\tau_E} = \underline{\phi}^{\alpha}(-\alpha)\phi_*^{-\alpha-1}*\frac{\partial\phi_*}{\partial\tau_E} > 0$$

Lemma b2: $(\frac{\partial\Psi_1}{\partial\tau_E}+\frac{\partial\Psi_2}{\partial\tau_E})*(\Gamma_1+\Gamma_2)-(\frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\partial\Gamma_2}{\partial\tau_E})*(\Psi_1+\Psi_2)=0$

From definitions we have:

$$\Psi_1=\frac{\beta^h Y}{\omega}\Gamma_1$$
$$\Psi_2=\frac{\beta^h Y}{\omega}\Gamma_2$$
$$\frac{\partial\Psi_1}{\partial\tau_E}=\frac{\beta^h Y}{\omega}\frac{\partial\Gamma_1}{\partial\tau_E}$$
$$\frac{\partial\Psi_2}{\partial\tau_E}=\frac{\beta^h Y}{\omega}\frac{\partial\Gamma_2}{\partial\tau_E}$$

With these equations, we have:

$$\left(\frac{\partial\Psi_1}{\partial\tau_E}+\frac{\partial\Psi_2}{\partial\tau_E}\right)\cdot(\Gamma_1+\Gamma_2)-\left(\frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\partial\Gamma_2}{\partial\tau_E}\right)\cdot(\Psi_1+\Psi_2)=$$
$$\left(\frac{\beta^h Y}{\omega}\frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\beta^h Y}{\omega}\frac{\partial\Gamma_2}{\partial\tau_E}\right)\cdot(\Gamma_1+\Gamma_2)-\left(\frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\partial\Gamma_2}{\partial\tau_E}\right)\cdot\left(\frac{\beta^h Y}{\omega}\Gamma_1+\frac{\beta^h Y}{\omega}\Gamma_2\right)=0$$

Having established Lemma b1 and Lemma b2, we can now conclude that the derivative of M^h with respect to τ^E can be written as:

$$\frac{\partial M^h}{\partial\tau^E}=\frac{-\left(f^P\frac{\partial\Psi_3}{\partial\tau^E}\right)\cdot\left(1-\frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2}\right)}{\left(f^P\Psi_3+F_{\text{Entry}}\right)^2}.$$

Based on Lemma b1, both Ψ_3 and its derivative with respect to τ^E are positive. Consequently, the term $f^P\frac{\partial\Psi_3}{\partial\tau^E}$ is positive. The expression $1-\frac{\sigma-1}{\sigma}\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2}$ is also positive since $\frac{\sigma-1}{\sigma}<1$ and $\frac{\Psi_1+\Psi_2}{\Gamma_1+\Gamma_2}<1$. As the denominator $\left(f^P\Psi_3+F_{\text{Entry}}\right)^2$ is a positive square and the numerator is negative, the entire fraction $\frac{\partial M^h}{\partial\tau^E}$ is negative.

Proof of (c):

We begin by expressing the sectoral price index using equation 2:

$$\left(P^T\right)^{1-\sigma}=M^T\left(\int_{\phi}^{\phi^*}\left(p^{ON}(\phi)\right)^{1-\sigma}dF(\phi)+\int_{\phi^*}^{\infty}\left(p^{TC}(\phi)\right)^{1-\sigma}dF(\phi)\right)$$

and we know:

- $dF(\phi)=\alpha\left(\frac{\phi^\alpha}{\phi^{\alpha+1}}d\phi\right)$
- $p^{ON}(\phi)=\frac{\kappa^{\frac{1}{1-\sigma}}w\tau_E}{\phi}$ from equation 6
- $p^{HF}(\phi)=\frac{\kappa^{\frac{1}{1-\sigma}}w}{\phi}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{-1}{\theta}}$ from equation 8

This allows us to rewrite the price index equation as:

$$P_R=\left(M_R\Gamma_1+M_R\Gamma_2\right)^{\frac{1}{1-\sigma}}$$

where Γ_1 and Γ_2 are defined as before:

$$\Gamma_1 = \alpha\kappa w^{1-\sigma}\tau_E^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{\sigma-\alpha-1}\left[\phi_*^{\sigma-\alpha-1}-\underline{\phi}^{\sigma-\alpha-1}\right]$$
$$\Gamma_2 = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}\phi_*^{\sigma-\alpha-1}$$

Lemma c1: $\Gamma_1 > 0$ **and** $\frac{\partial\Gamma_1}{\partial\tau_E} < 0$**.**

$$\Gamma_1 = \underbrace{\alpha\kappa w^{1-\sigma}\tau_E^{1-\sigma}\underline{\phi}^{\alpha}}_{\text{positive sign}}\cdot\underbrace{\frac{1}{\sigma-\alpha-1}}_{\text{negative sign}}\cdot\underbrace{\left[\phi_*^{\sigma-\alpha-1}-\underline{\phi}^{\sigma-\alpha-1}\right]}_{\text{negative sign}} > 0$$

Taking the derivative of Γ_1 with respect to τ_E:

$$\frac{\partial\Gamma_1}{\partial\tau_E} = \frac{\partial\Gamma_1}{\partial\tau_E}+\frac{\partial\Gamma_1}{\partial\phi_*}*\frac{\partial\phi_*}{\partial\tau_E}$$
$$\frac{\partial\Gamma_1}{\partial\tau_E} = \underbrace{\alpha\kappa w^{1-\sigma}(1-\sigma)\tau_E^{-\sigma}\underline{\phi}^{\alpha}\frac{1}{\sigma-\alpha-1}\left[\phi_*^{\sigma-\alpha-1}-\underline{\phi}^{\sigma-\alpha-1}\right]}_{\text{negative sign}}$$
$$+\underbrace{\alpha\kappa w^{1-\sigma}\tau_E^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{\sigma-\alpha-1}(\sigma-\alpha-1)\phi_*^{\sigma-\alpha-2}}_{\text{positive sign}}\cdot\underbrace{\frac{\partial\phi_*}{\partial\tau_E}}_{\text{negative sign}} \Rightarrow \frac{\partial\Gamma_1}{\partial\tau_E} < 0$$

Lemma c2: $\Gamma_2 > 0$ **and** $\frac{\partial\Gamma_2}{\partial\tau_E} = ?$**.**

$$\Gamma_2 = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}\phi_*^{\sigma-\alpha-1} > 0$$

As all terms are positive then Γ_2 is also positive.

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \frac{\partial\Gamma_2}{\partial\tau_E}+\frac{\partial\Gamma_2}{\partial\phi_*}*\frac{\partial\phi_*}{\partial\tau_E}$$
$$\frac{\partial\Gamma_2}{\partial\tau_E} = \underbrace{\alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\frac{\sigma-1}{\theta}\right)\left(-\theta\tau_E^{-\theta-1}\right)\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-\theta-1}{\theta}}\phi_*^{\sigma-\alpha-1}}_{\text{negative sign}}$$
$$+\underbrace{\alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}(\sigma-\alpha-1)\phi_*^{\sigma-\alpha-2}}_{\text{negative sign}}\cdot\underbrace{\frac{\partial\phi_*}{\partial\tau_E}}_{\text{negative sign}}$$

Therefore, $\frac{\partial\Gamma_2}{\partial\tau_E}$ comprises both negative and positive terms, making its overall sign dependent on the relative magnitude of these components. To analyze this further, I factor the expression as follows:

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\frac{1}{1+\alpha-\sigma}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-\theta-1}{\theta}}\phi_*^{\sigma-\alpha-2}\left[(1-\sigma)\tau_E^{-\theta-1}\phi_* + \left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)(\sigma-\alpha-1)\frac{\partial\phi_*}{\partial\tau_E}\right]$$

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-\theta-1}{\theta}}\phi_*^{\sigma-\alpha-2}\left[\frac{1-\sigma}{1+\alpha-\sigma}\tau_E^{-\theta-1}\phi_* - \left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)\frac{\partial\phi_*}{\partial\tau_E}\right]$$

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-\theta-1}{\theta}}\phi_*^{\sigma-\alpha-1}\left[\frac{1-\sigma}{1+\alpha-\sigma}\tau_E^{-\theta-1} - \left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)\frac{1}{\phi_*}\frac{\partial\phi_*}{\partial\tau_E}\right]$$

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}\phi_*^{\sigma-\alpha-1}\left[\frac{1-\sigma}{1+\alpha-\sigma}\frac{\tau_E^{-\theta-1}}{\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)} - \frac{1}{\phi_*}\frac{\partial\phi_*}{\partial\tau_E}\right]$$

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \alpha\kappa w^{1-\sigma}\underline{\phi}^{\alpha}\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{\frac{\sigma-1}{\theta}}\phi_*^{\sigma-\alpha-1}\frac{1}{\tau_E}\left[\frac{1-\sigma}{1+\alpha-\sigma}\frac{\tau_E^{-\theta}}{\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)} - \frac{\tau_E}{\phi_*}\frac{\partial\phi_*}{\partial\tau_E}\right]$$

Let $E_{\tau_E}^{\phi_*}$ denote the elasticity of ϕ_* with respect to τ_E. Since all terms outside the bracket are positive, the sign of Lemma 2b is then determined as follows:

$$\frac{\partial\Gamma_2}{\partial\tau_E} = \begin{cases} < 0 & \text{if } E_{\tau_E}^{\phi_*} < \frac{\sigma-1}{1+\alpha-\sigma}\frac{\tau_E^{-\theta}}{\tau_P^{-\theta}+\tau_E^{-\theta}} \\ > 0 & \text{if } E_{\tau_E}^{\phi_*} > \frac{\sigma-1}{1+\alpha-\sigma}\frac{\tau_E^{-\theta}}{\tau_P^{-\theta}+\tau_E^{-\theta}} \\ = 0 & \text{if } E_{\tau_E}^{\phi_*} = \frac{\sigma-1}{1+\alpha-\sigma}\frac{\tau_E^{-\theta}}{\tau_P^{-\theta}+\tau_E^{-\theta}} \end{cases}$$

To conceptually analyze the impact of a decrease in τ on the price index, we must consider how it affects the prices set by each firm through two main channels.

First, for any given firm—whether online-only or hybrid—a decrease in τ leads to a reduction in prices if the firm remains in the same delivery mode.

Second, some firms may shift from being hybrid to online as the productivity threshold ϕ^* decreases. For these firms, prices may increase because they transition from the hybrid to the online mode.

The overall impact on the price index depends on which effect is more dominant. The influence of the second channel is determined by the elasticity of ϕ^* with respect to τ. If this elasticity is low, the first effect will dominate, meaning that a decrease in τ will lead to a decrease in the price index.

We have to show:

$$-\frac{\tau_E}{\phi_*}\frac{\partial\phi_*}{\partial\tau_E} < \frac{\sigma-1}{1+\alpha-\sigma}\frac{\tau_E^{-\theta}}{\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)}$$

We will have

$$T_1 = -(\sigma-1)\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{-1}\tau_E^{-\theta-1}$$
$$T_2 = \frac{(\sigma-\alpha-1)}{\phi^*}\frac{\partial\phi^*}{\partial\tau_E}$$

We have to show that
$$\frac{T_2}{|T_1|} < 1$$
We define:
$$C = \tau_P^{-\theta} + \tau_E^{-\theta}$$
$$D = (\phi^*)^{-1} \frac{\partial \phi^*}{\partial \tau_E}$$
Thus:
$$\frac{T_2}{|T_1|} = \frac{\frac{(\sigma-\alpha-1)}{\phi^*}\frac{\partial \phi^*}{\partial \tau_E}}{(\sigma-1)\left(\tau_P^{-\theta}+\tau_E^{-\theta}\right)^{-1}\tau_E^{-\theta-1}} = \frac{(\sigma-\alpha-1)CD}{(\sigma-1)\tau_E^{-\theta-1}}$$
C is bounded by $1+\tau_P^{-\theta}$. Assuming $|D|$ is bounded by a constant K that depends only on exogenous parameters, i.e., $|D| \leq |K|$:
$$\frac{T_2}{|T_1|} \leq \frac{(1+\alpha-\sigma)\left(1+\tau_P^{-\theta}\right)|K|\tau_E^{\theta+1}}{(\sigma-1)}$$
For the negative term to dominate:
$$\frac{T_2}{|T_1|} < 1$$
This implies:
$$\frac{(1+\alpha-\sigma)\left(1+\tau_P^{-\theta}\right)|K|\tau_E^{\theta+1}}{(\sigma-1)} < 1$$
Solving for τ_E:
$$\tau_E^{\theta+1} < \frac{(\sigma-1)}{(1+\alpha-\sigma)\left(1+\tau_P^{-\theta}\right)|K|}$$
Since $\theta+1>0$, $\tau_E^{\theta+1}$ increases with τ_E. Therefore, the inequality holds for τ_E less than a critical value τ_E^*:
$$\tau_E < \left(\frac{(\sigma-1)}{(1+\alpha-\sigma)\left(1+\tau_P^{-\theta}\right)|K|}\right)^{\frac{1}{\theta+1}}$$

Having established both lemma c1 and lemma c2, we differentiate the price index, P_R, with respect to τ_E:
$$\frac{dP_R}{d\tau} = \frac{1}{1-\sigma}\left(M_R\Gamma_1 + M_R\Gamma_2\right)^{\frac{\sigma}{1-\sigma}} \cdot \left[\frac{dM_R}{d\tau}(\Gamma_1+\Gamma_2) + M_R\left(\frac{d\Gamma_1}{d\tau}+\frac{d\Gamma_2}{d\tau}\right)\right]$$

We know that $\frac{1}{1-\sigma} < 0$ and $(M_R\Gamma_1 + M_R\Gamma_2)^{\frac{\sigma}{1-\sigma}} > 0$. Also, we know the expression inside the brackets is negative. This is because, as shown in part (b), $\frac{dM_R}{d\tau_E}$ is negative, and from Lemma C1 and Lemma C2, we established that $\frac{\partial \Psi_1}{\partial \tau_E} < 0$ and $\frac{\partial \Psi_2}{\partial \tau_E} < 0$. Therefore, the sign of $\frac{dP_R}{d\tau_E}$ is positive.

Appendix A6. 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:

A6.1. **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.

A6.2. **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).

A6.3. **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.

A6.4. **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.

A6.5. **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 A43 shows the results. As you can see Urbanisation, population and GDP level are the most important contributors to predicting the rollout date.

Appendix A7. Graphs

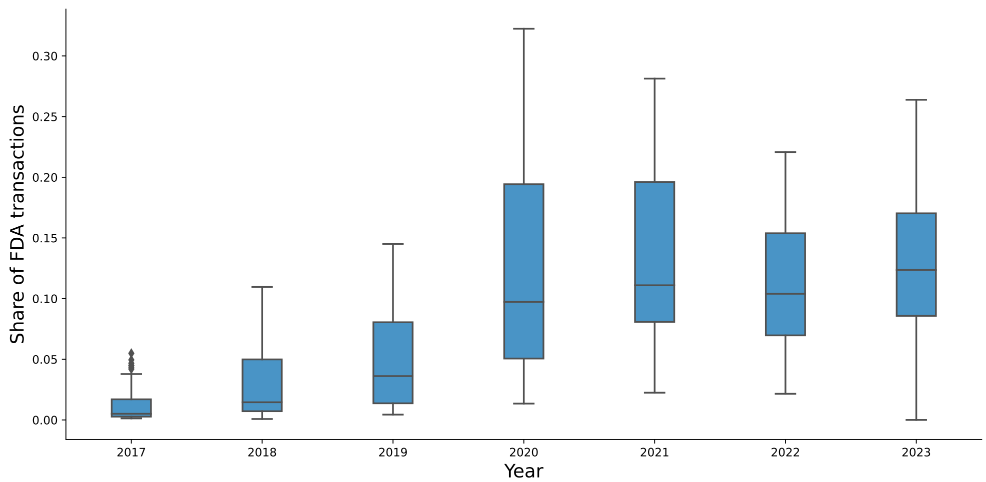
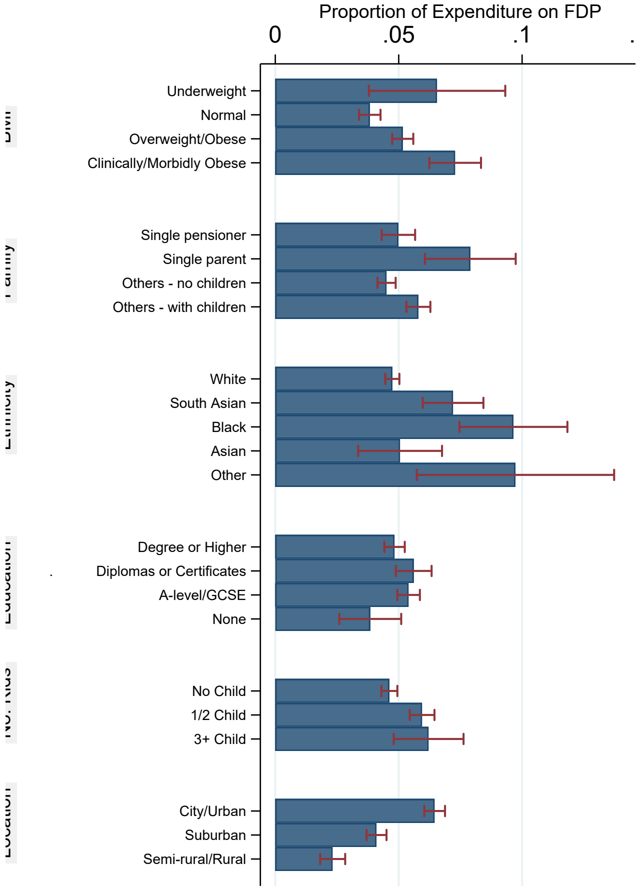
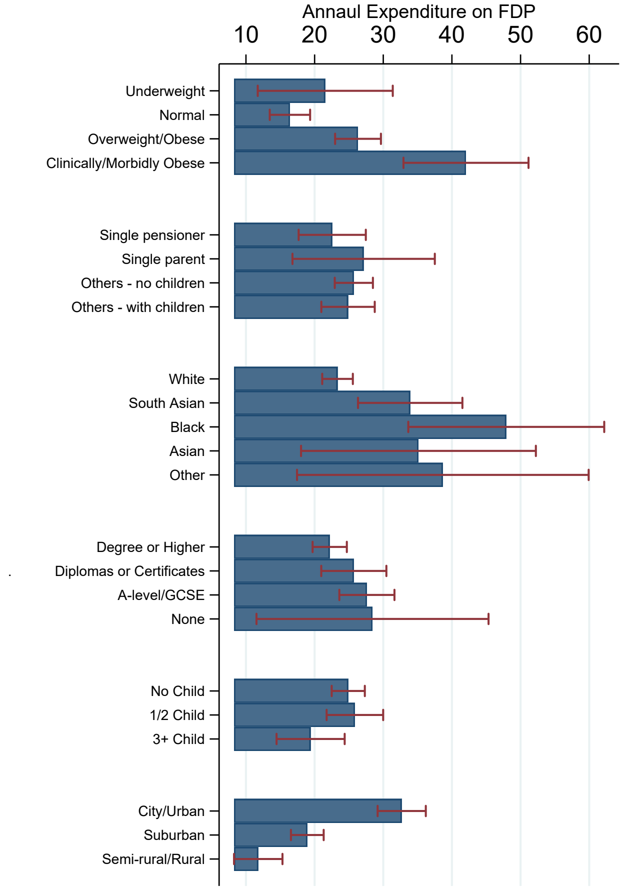


Figure A1. *Notes:* The figure shows a box-and-whisker plot depicting the penetration of UberEats and Deliveroo across ONS subgroups over time. The y-axis represents the share of FDA transactions, while the x-axis shows the years from 2017 to 2023. Data reflects the distribution and trends in the adoption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

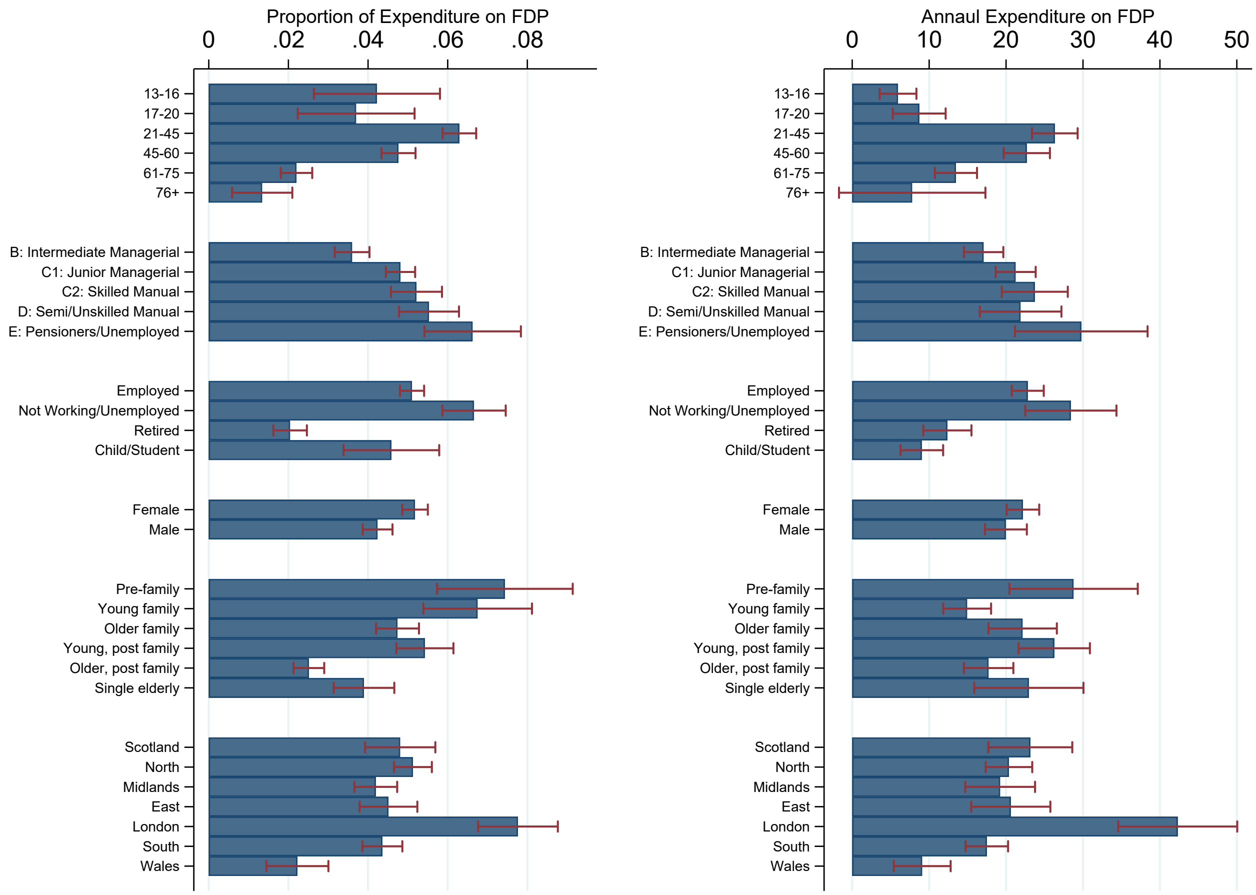


(a) Share of FDP from all Restaurant Spending



(b) Annual Spending on FDP

Figure A2. *Notes:* This figure shows the proportion of expenditure directed towards FDPs (panel (a)) and the expenditure on FDPs (panel (b)), disaggregated by various demographic factors including education, ethnicity, and BMI of the main shopper, self-reported degree of concern for a personal healthy lifestyle, family structure, number of children, and urban/rural residency. It utilizes 2022 data from Kantar's Worldpanel Take Home Purchase Panel.



(a) Share of FDP from all Restaurant Spending

(b) Annual Spending on FDP

Figure A3. *Notes:* This figure shows the proportion of expenditure directed towards FDPs (panel (a)) and the expenditure on FDPs (panel (b)), disaggregated by various demographic factors including class, employment, age, gender, family lifecycle, and region. It utilizes data from Kantar's Worldpanel Out of Home Panel for the year 2022.

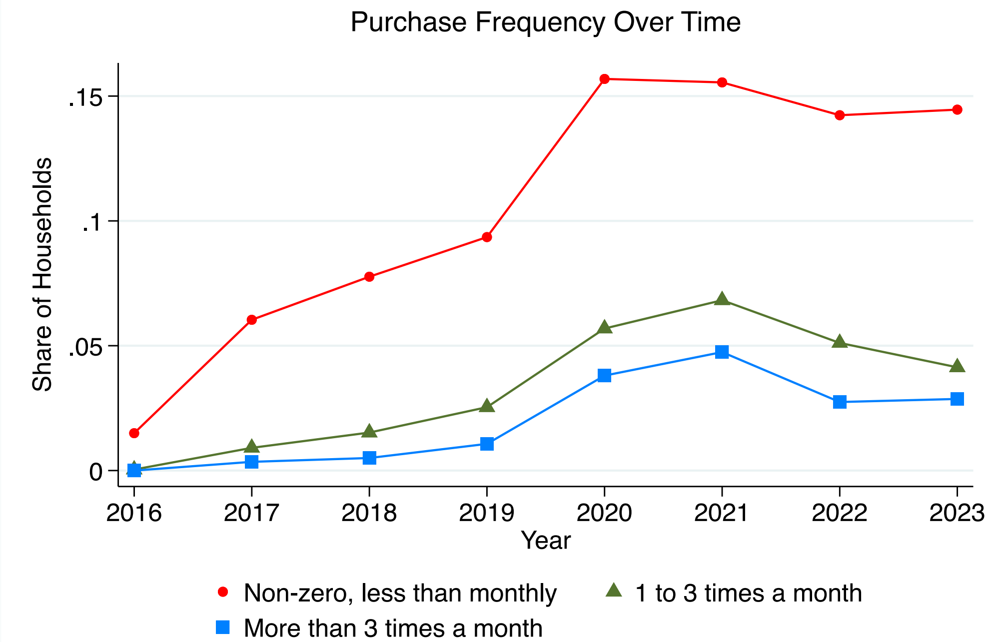
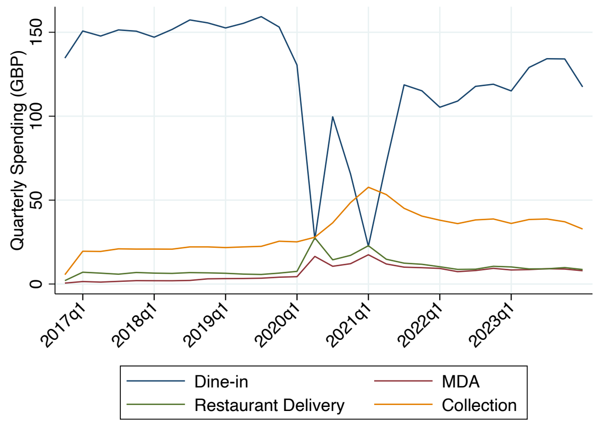
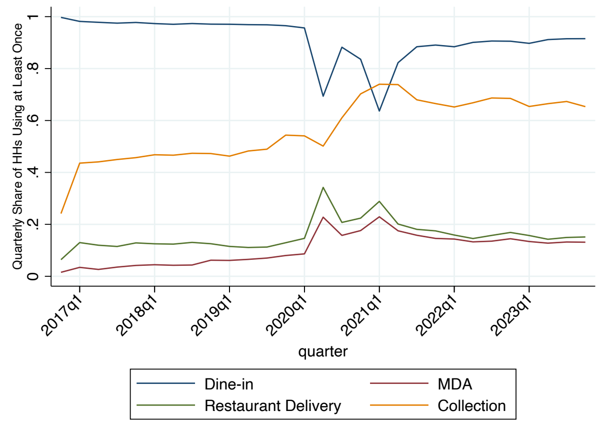


Figure A4. *Notes:* The graph illustrates the FDA purchase frequency distribution of households over time, categorizing purchase frequency into four groups: non-users, less than once a month, 1 to 3 times a month, and more than 3 times a month. The data is from Kantar's Worldpanel Out of Home Panel for the years 2016 to 2023.



(a) Spending



(b) Share of people using

Figure A5. *Notes:* This graph illustrates trends in household spending and usage of food service modes in Kantar's Worldpanel Out of Home Panel, for the years 2017 to 2023, segmented by the method of order fulfillment. Panels (a) and (b) show quarterly spending and usage trends, respectively. The first category includes orders not taken away from the premises. The second category encompasses orders made through food delivery platforms 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. 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.

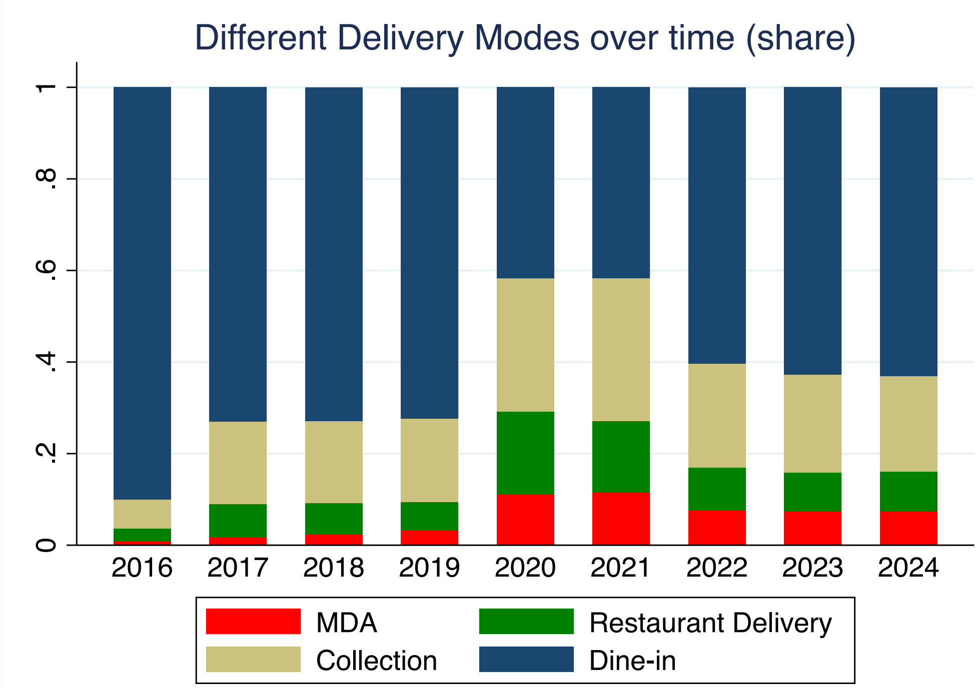
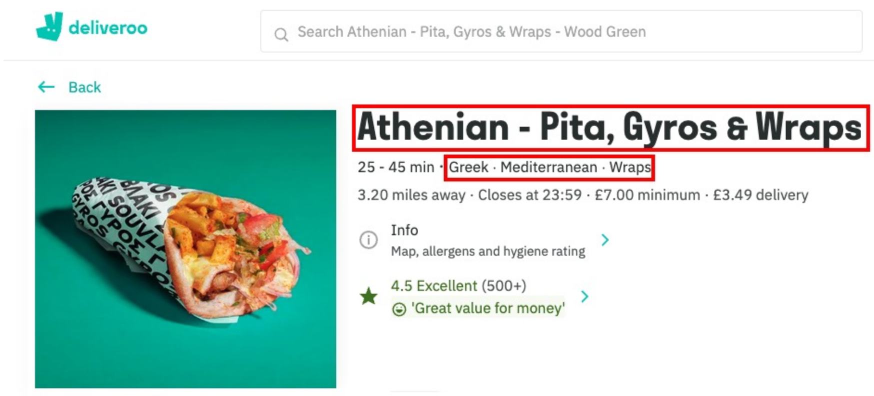
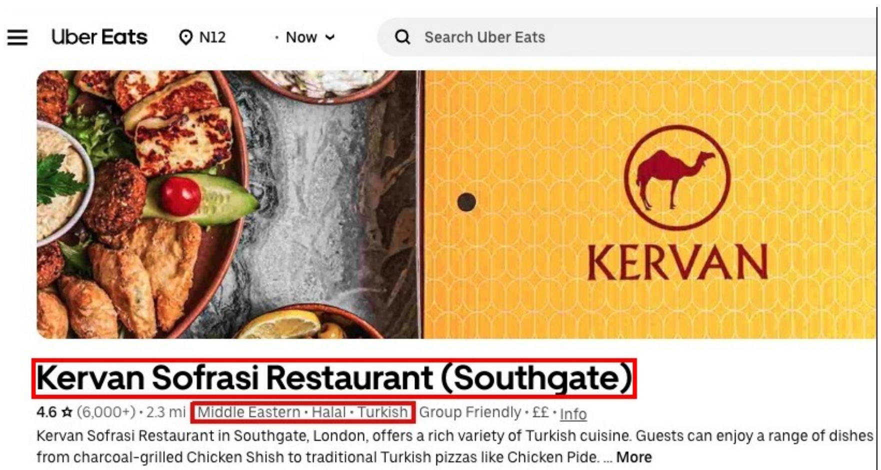


Figure A6. *Notes:* The graph depicts the distribution of delivery modes over time. The first category includes dine-in orders. The second category encompasses orders made through food delivery platforms from services Just Eat, Uber Eats, Deliveroo, Amazon Restaurants, and Hungry House. This category 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.

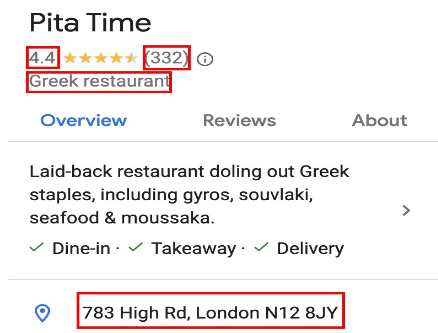


(a) Deliveroo

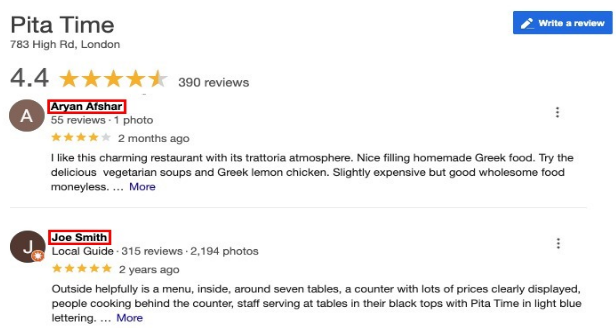


(b) UberEats

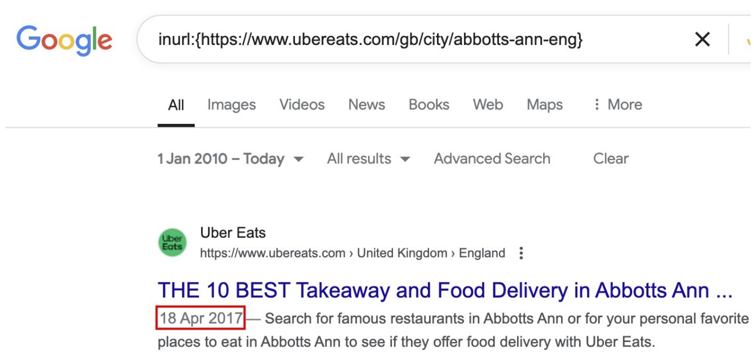
Figure A7. *Notes:* Panel (a) shows a sample restaurant on Deliveroo along with key information extracted from it, such as the name, rating, cuisine type, and address. Panel (b) displays the same procedure for a restaurant on UberEats.



(a) Google Maps



(b) Google Reviewers



(c) Google Indexed date

Figure A8. *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.

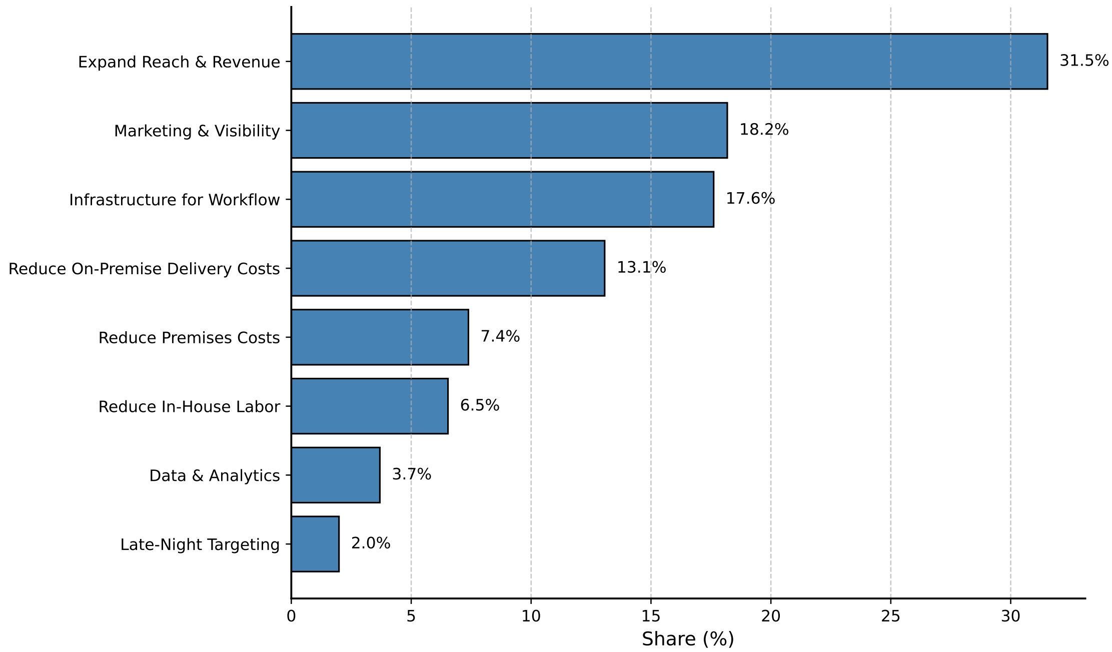


Figure A9. *Notes:* This figure illustrates the percentage distribution of identified reasons why restaurateurs consider partnering with food delivery apps, based on data from Reddit's r/restaurateur and r/restaurantowners subreddits. Posts mentioning relevant keywords indicative of using food apps (661 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.

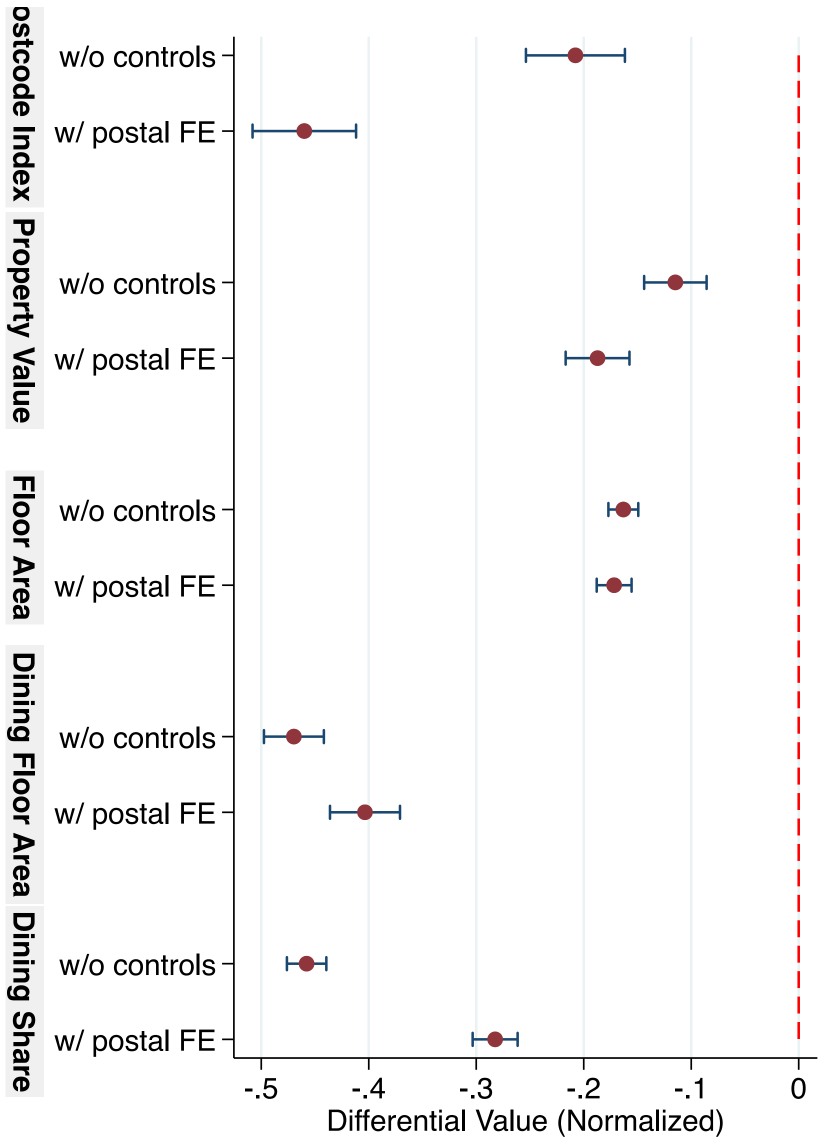
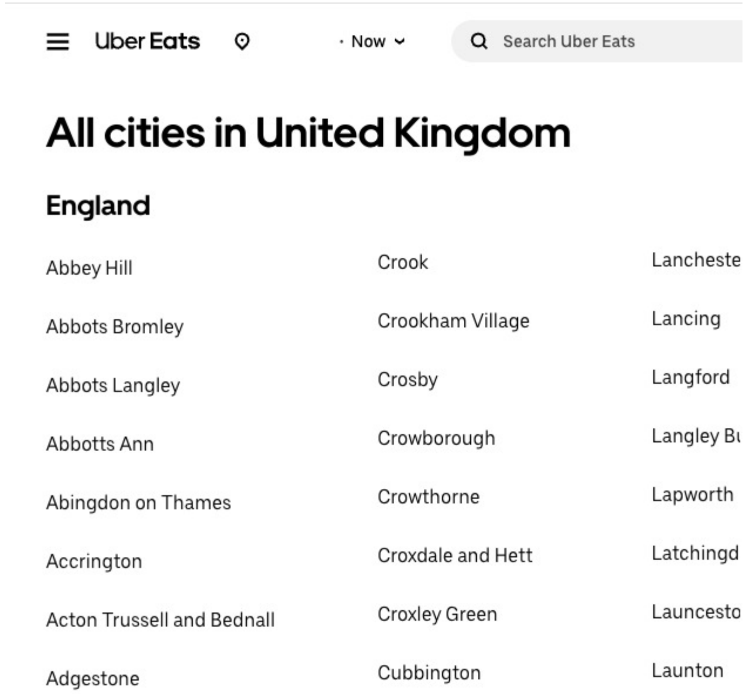
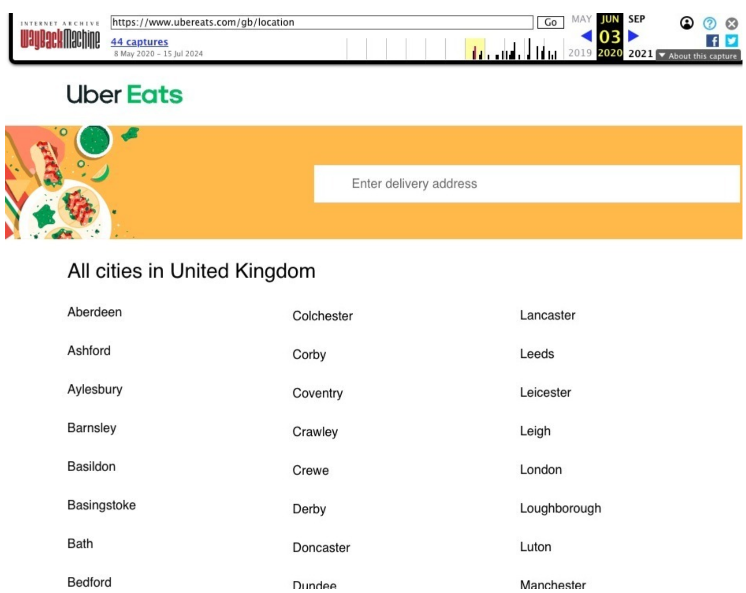


Figure A10. *Notes:* This graph presents the differences in property characteristics between restaurants listed on food delivery applications (FDA) and those not listed, among non-chain restaurants. The outcome variables include Price Index (estimated average property price within the restaurant's postcode), 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 FDA 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.

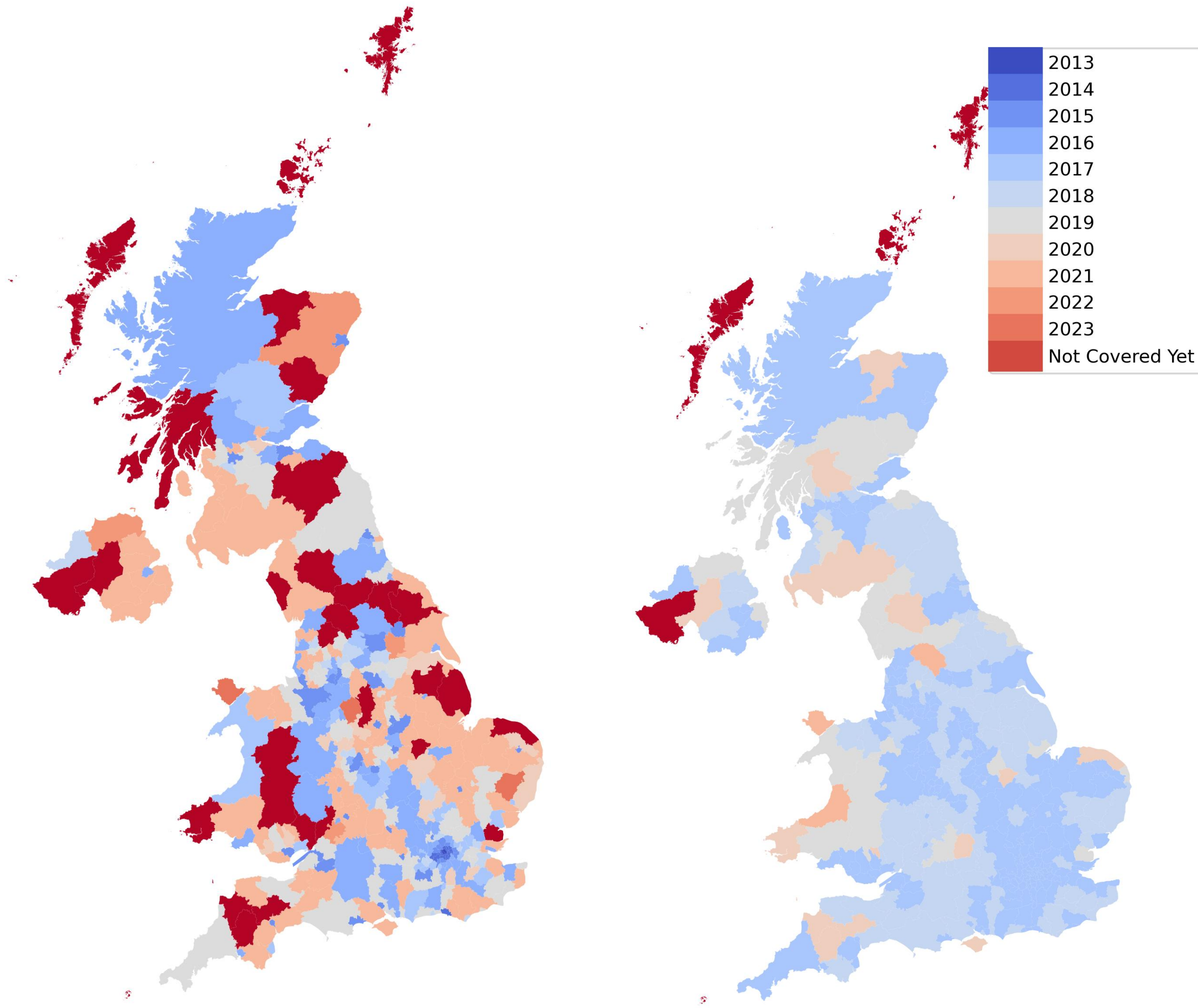


(a) UberEats Coverage Page



(b) Internet Archive

Figure A11. *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 A12. *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.

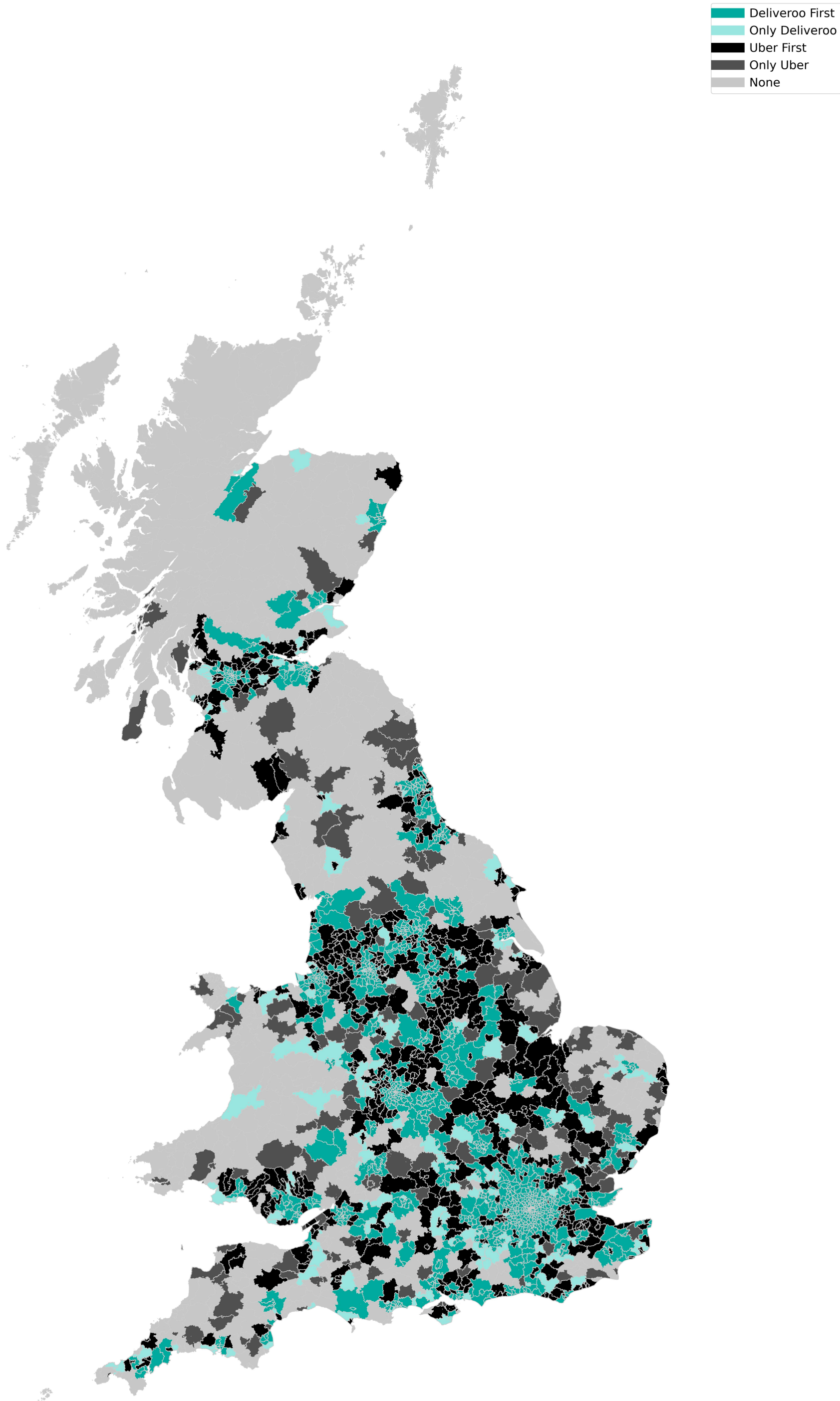
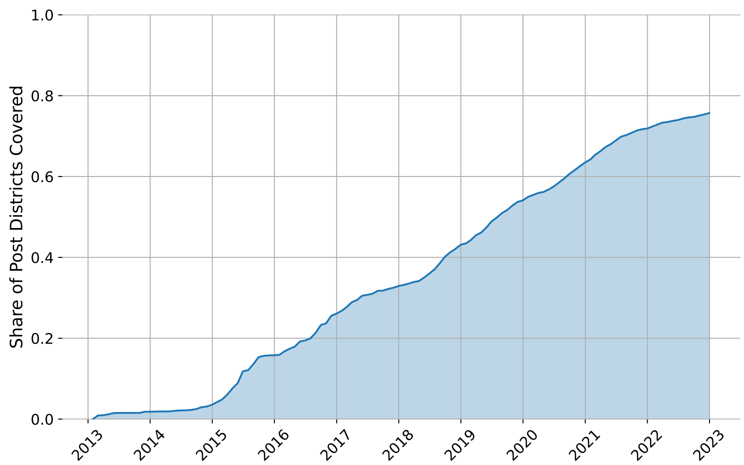
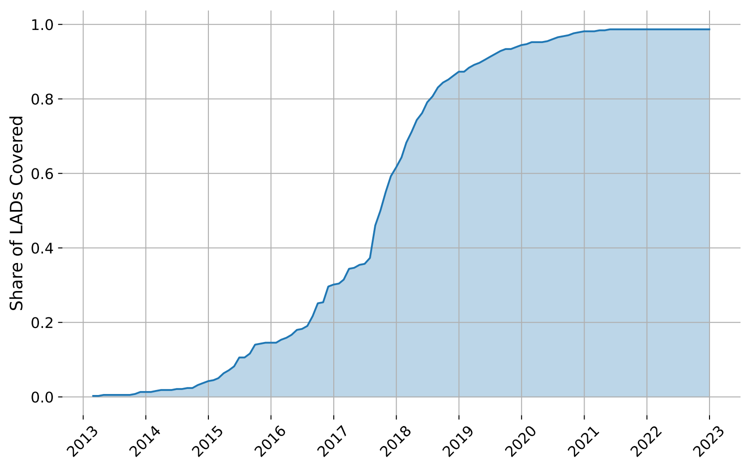


Figure A13. *Notes:* The map illustrates the rollout dynamics of Deliveroo and UberEats in UK postal districts, showing which platform entered first, which districts are only served by Deliveroo or Uber, and which districts are not served by either platform. Data is sourced from the author's scraping data collection.



(a) Share of Postal Districts Covered



(b) Share of LADs Covered

Figure A14. *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.

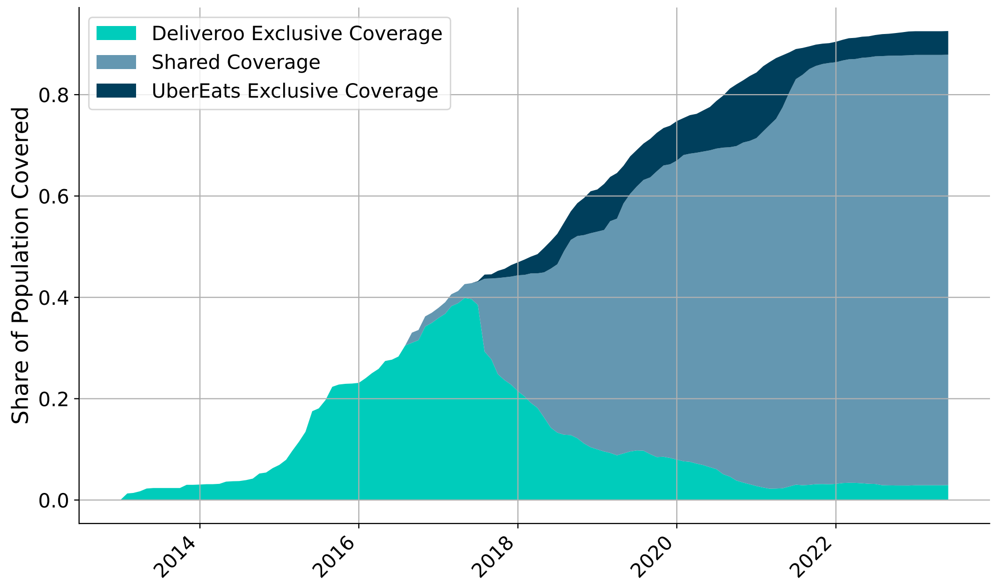
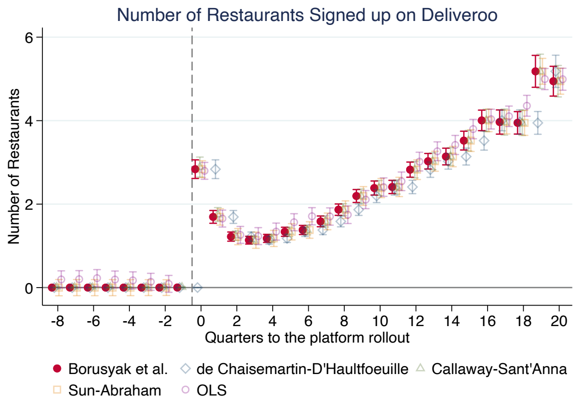
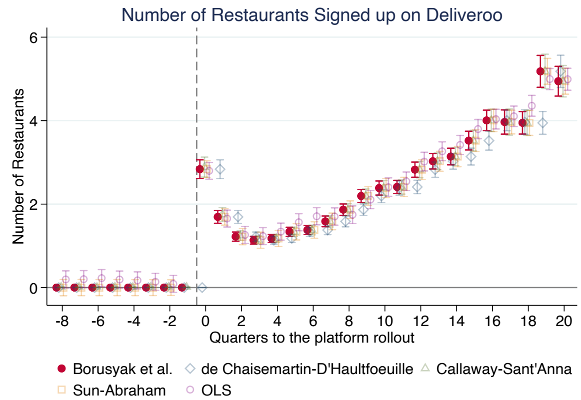


Figure A15. *Notes:* The figure illustrates the share of the population with access to Deliveroo (teal), UberEats (dark blue), and both services (light blue) over time. 'Having access' is defined for each postal district as detailed in the accompanying text, with population figures derived from the 2021 census.



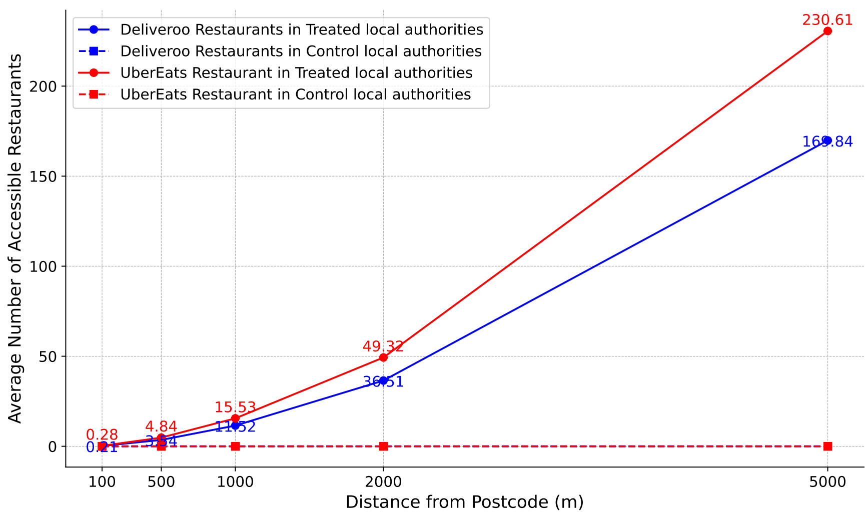
(a) New Restaurants Registered on Deliveroo



(b) New Restaurants Registered on Uber Eats

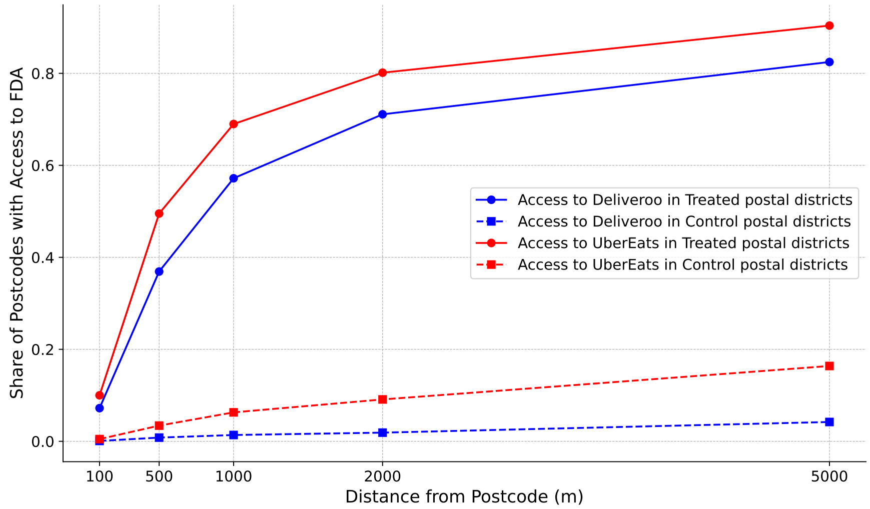
Figure A16. *Notes:* Panel (a) presents the event study results for Deliveroo, while panel (b) details those for UberEats. The analyzed outcome variable is number of new restaurants on the platform. Borusyak *et al.* (2023) estimator is used. Postcodes with Deliveroo rollout before 2017-03 (768 postcodes) are dropped since imputation is impossible for these units as they are treated in all periods in the sample. The analysis spacial units that have never been treated in the analysis. Each 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

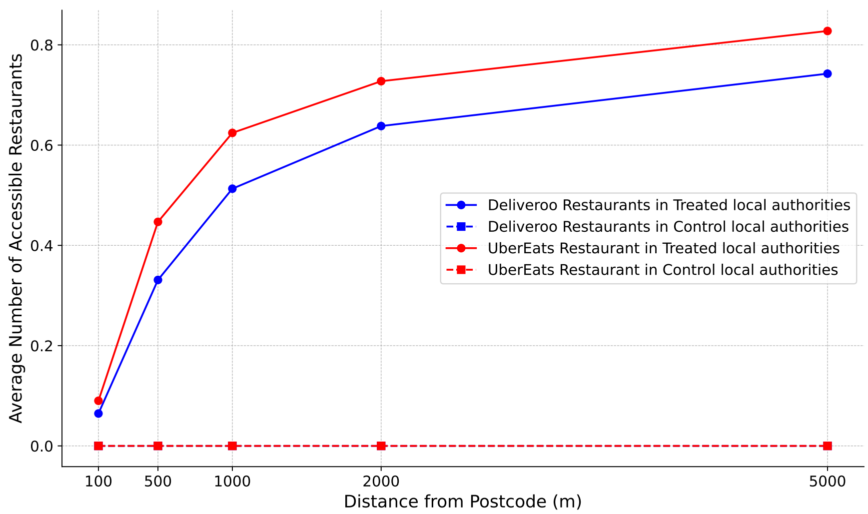


(b) Local Authority

Figure A17. *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.

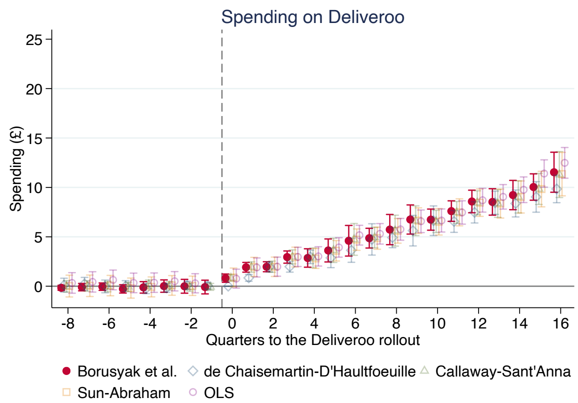


(a) Postal District

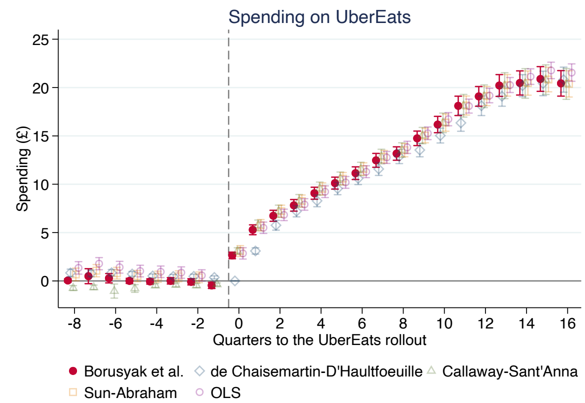


(b) Local Authority

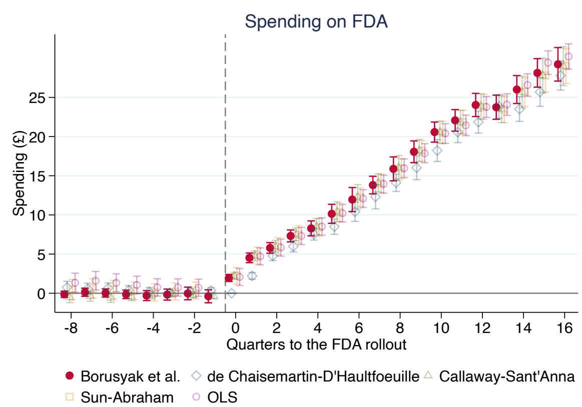
Figure A18. *Notes:* The figure illustrates the share of postcodes having access to FDA as a function of distance from postcodes, comparing postcodes in treated and control spatial units as of 2023. Panel (a) shows postcodes in treated and control postal districts, while panel (b) shows postcodes in 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

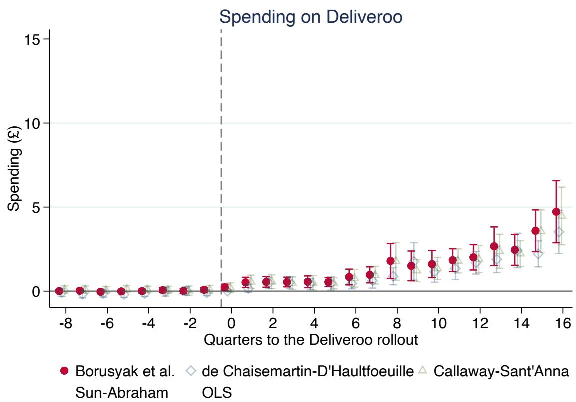


(b) UberEats Rollout Analysis

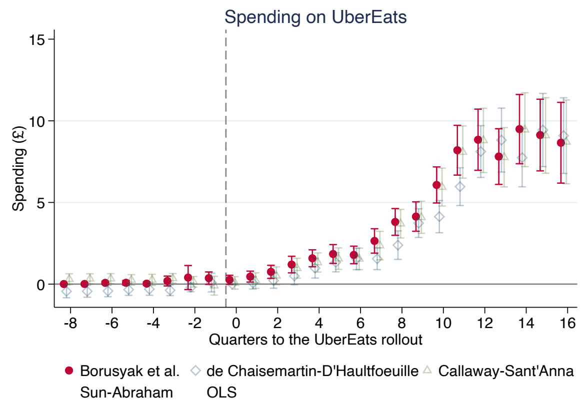


(c) Combined Platform Rollout Analysis

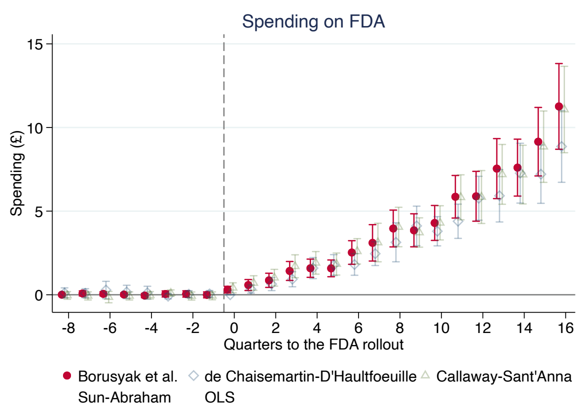
Figure A19. *Notes:* Panel (a) presents the event study results for the individual spending on Deliveroo following its rollout, panel (b) details the results for UberEats, and panel (c) shows the combined spending for Deliveroo and UberEats, based on the earliest rollout date of either platform. The outcome variable analyzed is expenditure, measured using the Fable dataset. The estimator from Borusyak *et al.* (2023) is used. The analysis includes spatial units that have never been treated.



(a) Deliveroo Rollout Analysis



(b) UberEats Rollout Analysis



(c) Combined Platform Rollout Analysis

Figure A20. *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 Out of Home Panel and Take Home Purchase Panel for years 2017 to 2023. The estimator from Borusyak *et al.* (2023) is used. The analysis includes spatial units that have never been treated.

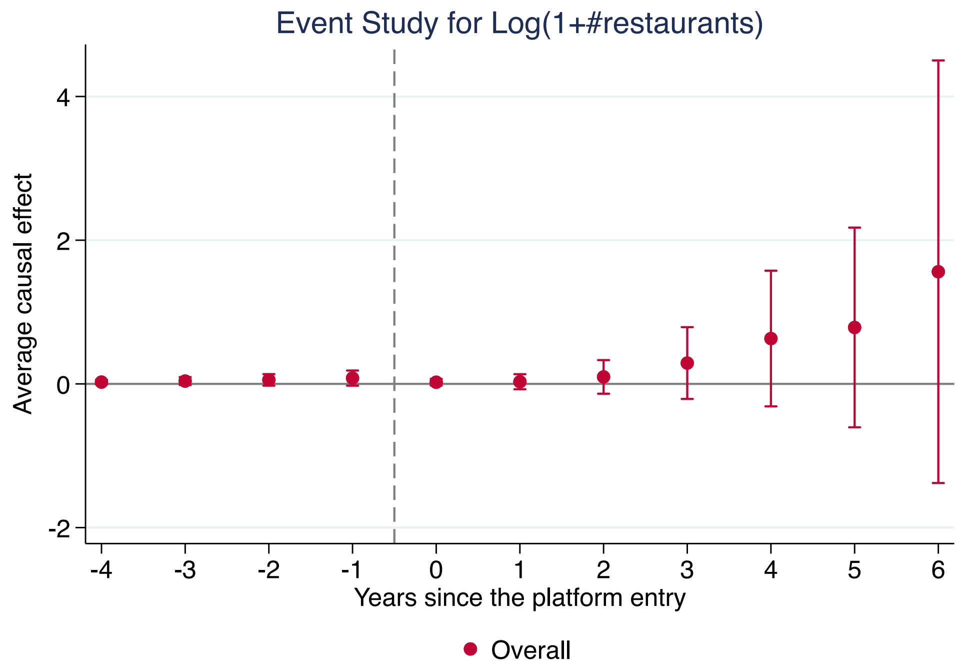
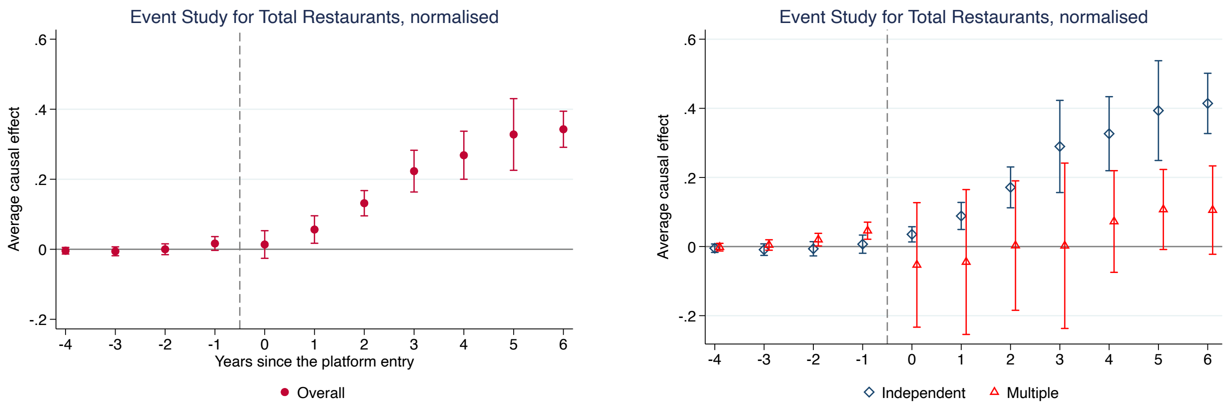


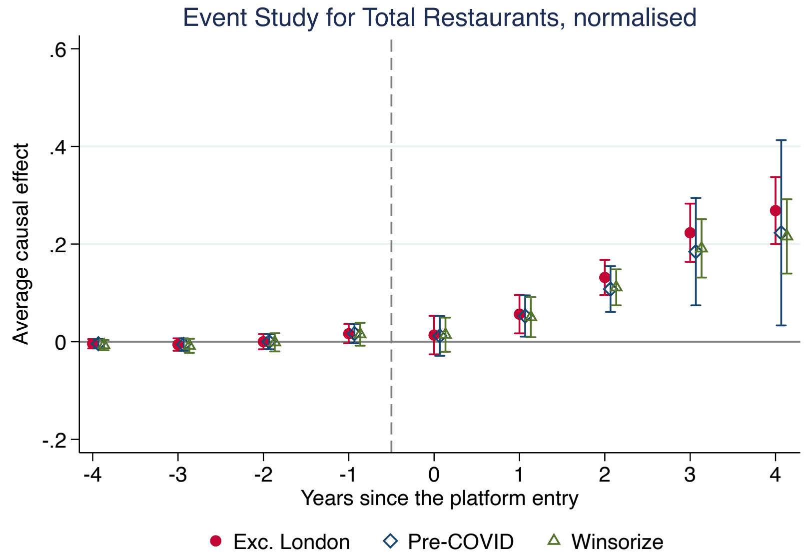
Figure A21. *Notes:* The figure shows the impact of food delivery platforms on the log transformation of the number of restaurants for different cuisine types, indicating changes in the number of establishments across various culinary categories. Cuisine types are categorized as outlined in Table A8. Data is sourced from the Local Data Company (LDC).



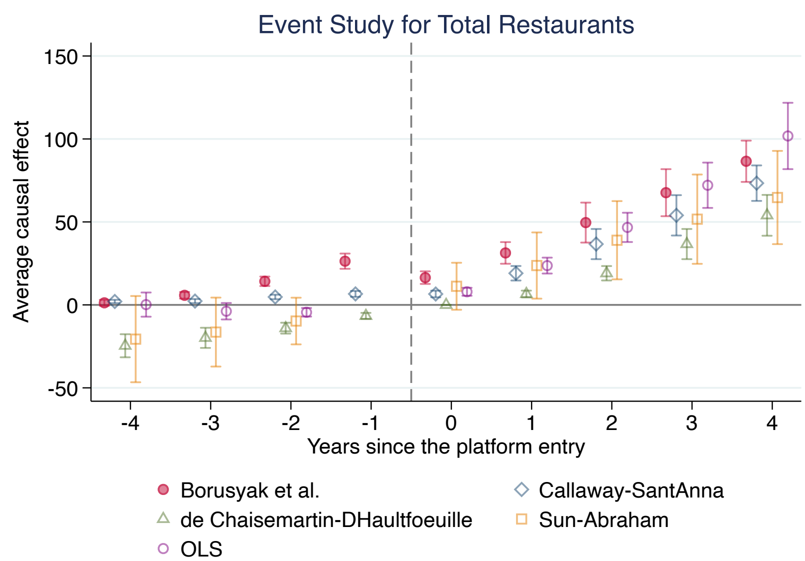
(a) Overall

(b) Independent vs Multiple

Figure A22. *Notes:* Panel (a) presents the average causal effect of food delivery platform rollout on the total number of restaurants over time as a percentage of the counterfactual outcome, absent food delivery platform (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 A23. *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.

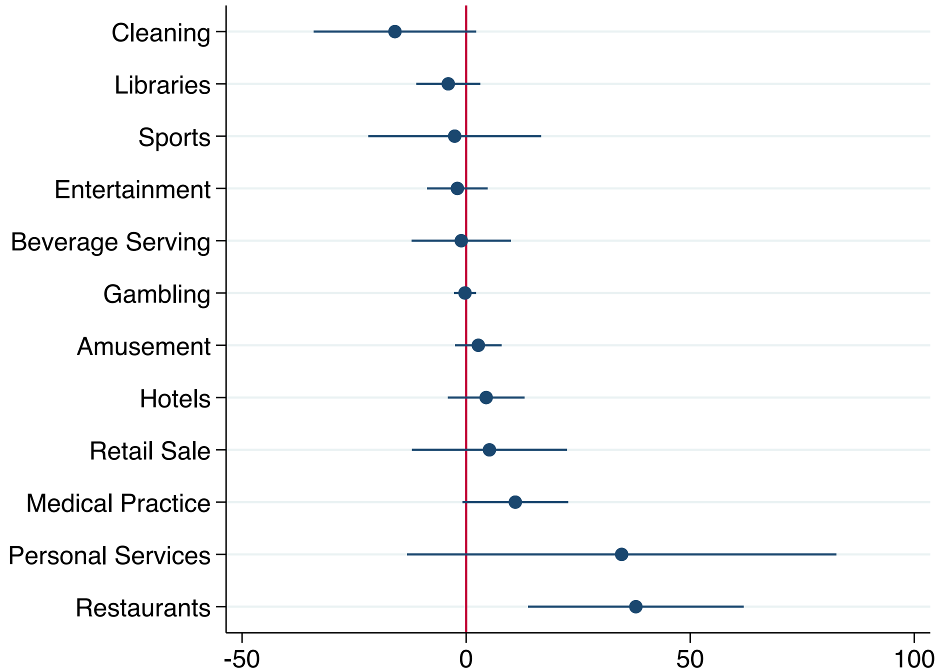


Figure A24. *Notes:* This figure displays the estimated effect of food delivery platform (FDP) rollout on the number of businesses in various placebo industries. Each coefficient represents the result of a separate regression, where the outcome variable is the number of businesses in a local authority, 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.

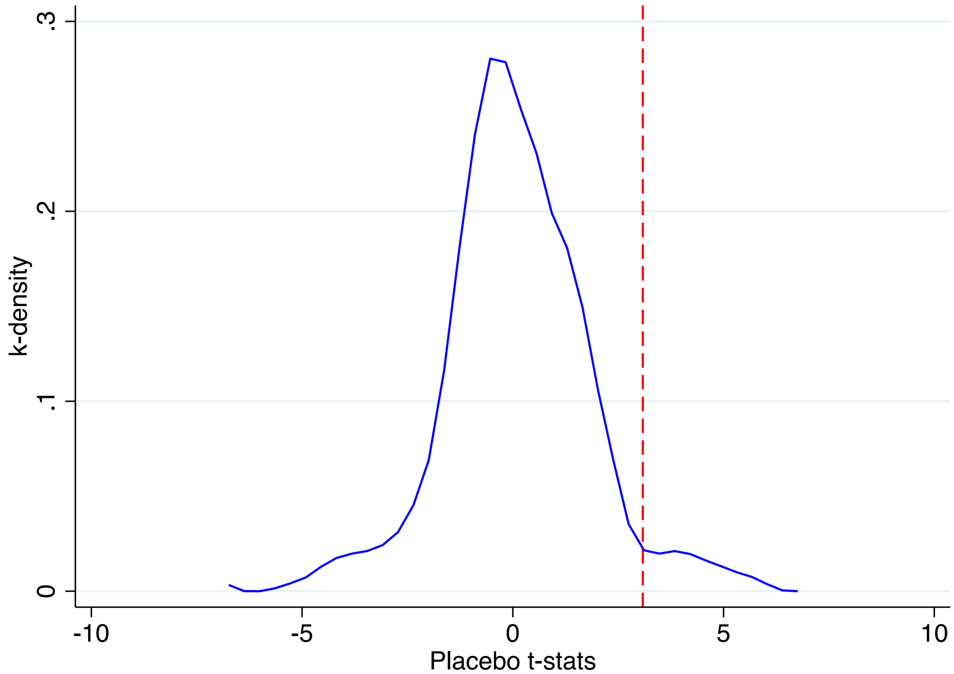


Figure A25. *Notes:* This figure presents the kernel density function of t-statistics for the effect of food delivery platform (FDP) rollout on the number of businesses across all three-digit SIC 2007 industries. The vertical line indicates the true point estimate for the restaurant industry. Data are sourced from the UK Business Counts from Nomis, which is an extract from the Inter-Departmental Business Register (IDBR), for the years 2010-2023.

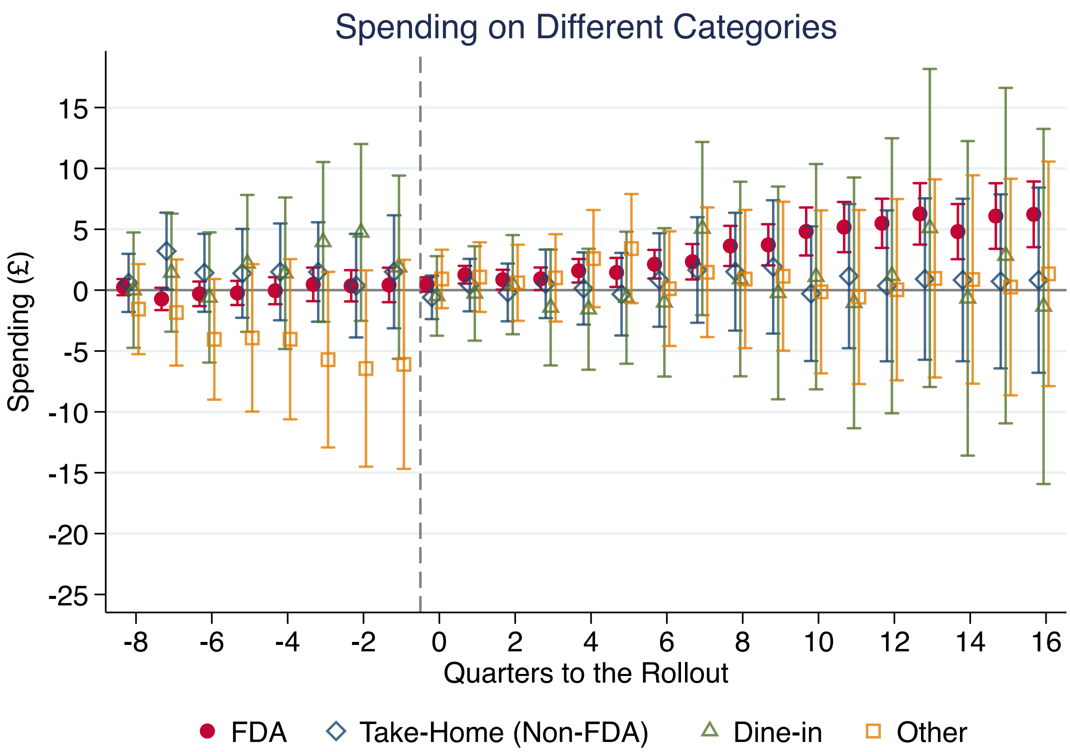
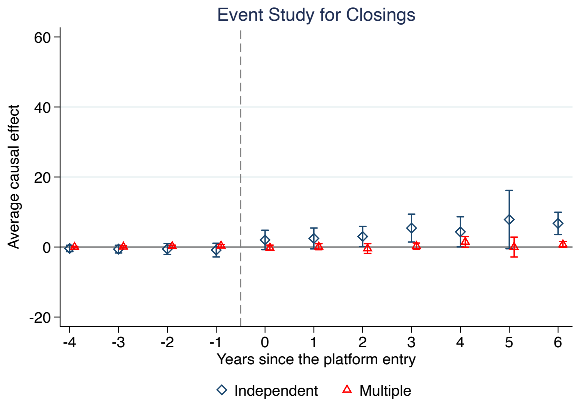
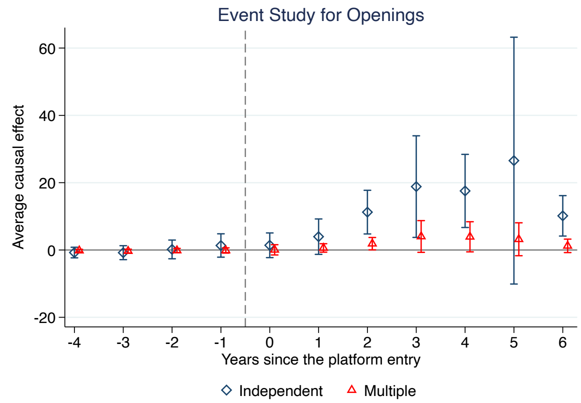


Figure A26. *Notes:* This graph shows the impact of the rollout of food delivery applications on different spending categories. Data is from Kantar's Worldpanel Out of Home Panel for years 2017 to 2023.

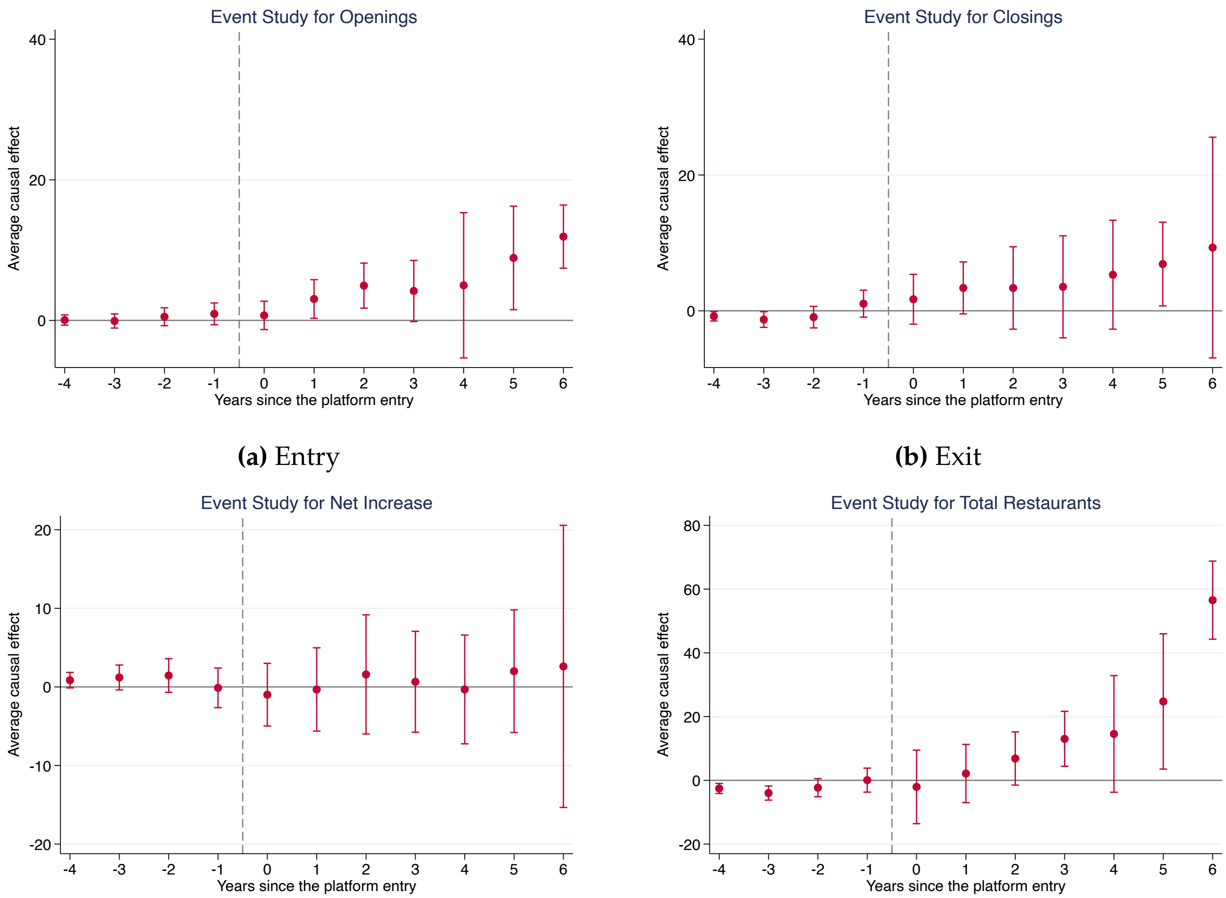


(a) Closings



(b) Openings

Figure A27. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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.



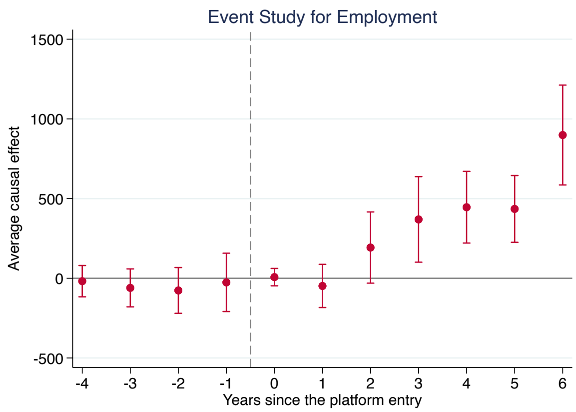
(a) Entry

(b) Exit

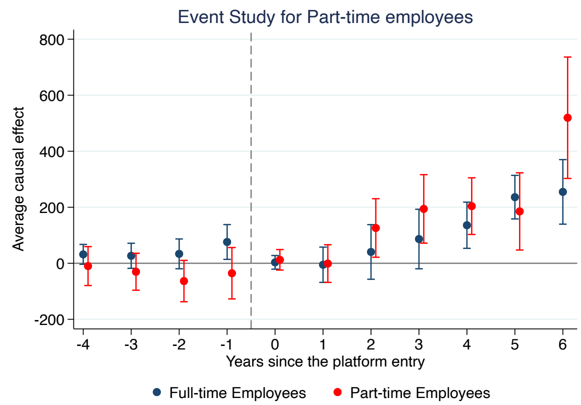
(c) Net-Creation (flow variable)

(d) Current Alive Businesses (stock variable)

Figure A28. *Notes:* This figure shows the average causal effect of food delivery platform rollout on restaurant dynamics at the Local Authority District (LAD) level. Panel (a) illustrates the number of entries per year, while panel (b) shows the number of exits. panel (c) presents net creation (flow variable), and panel (d) shows the number of currently alive businesses (stock variable). Data is sourced from Companies House, focusing on businesses with SIC codes 56101, 56102, and 56103, excluding restaurants operating as sole traders or partnerships.



(a) Overall Employment



(b) Part-time vs Full-time Employment

Figure A29. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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.

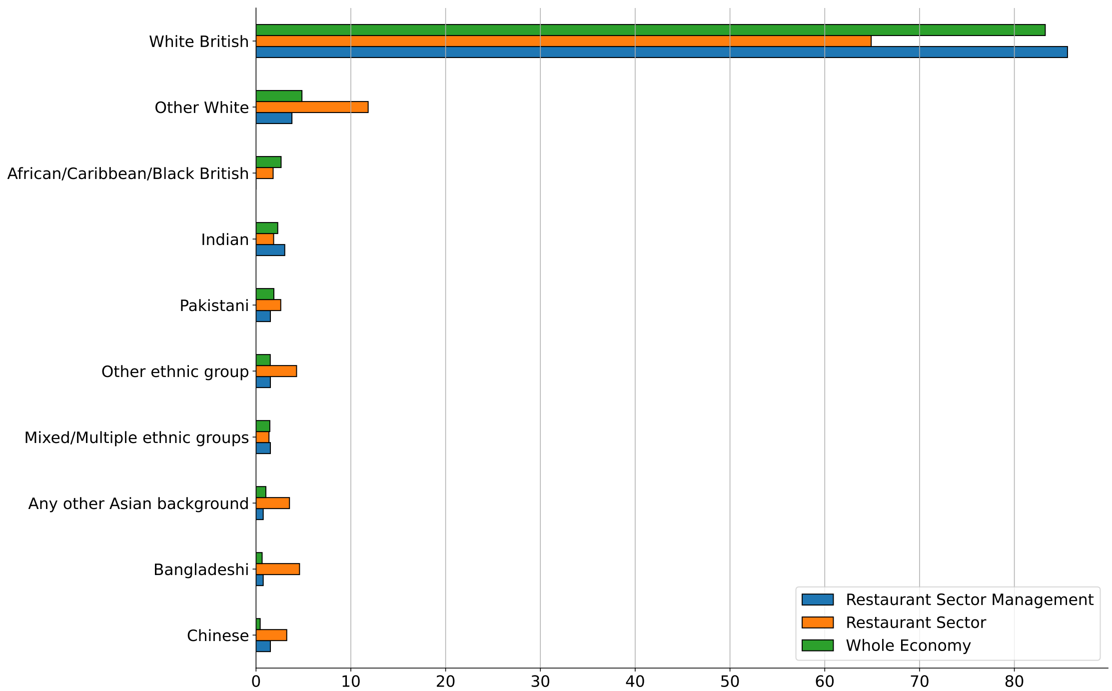
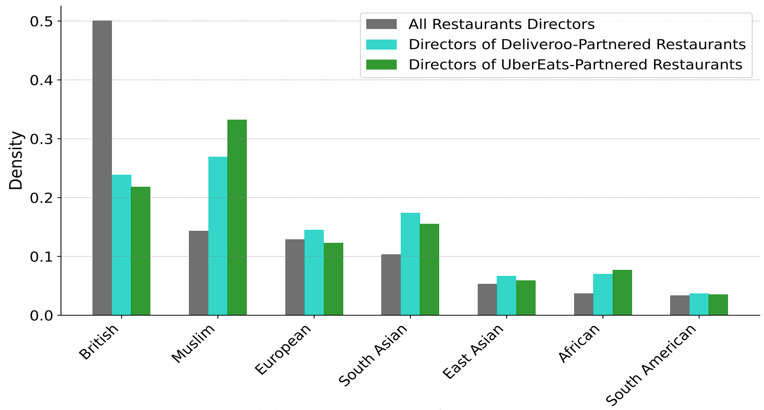
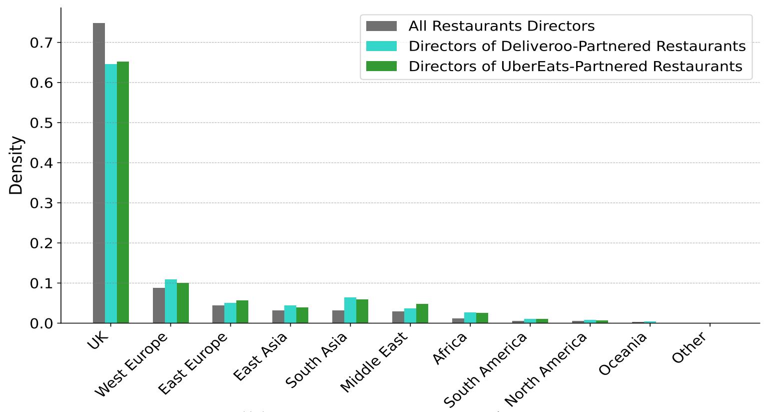


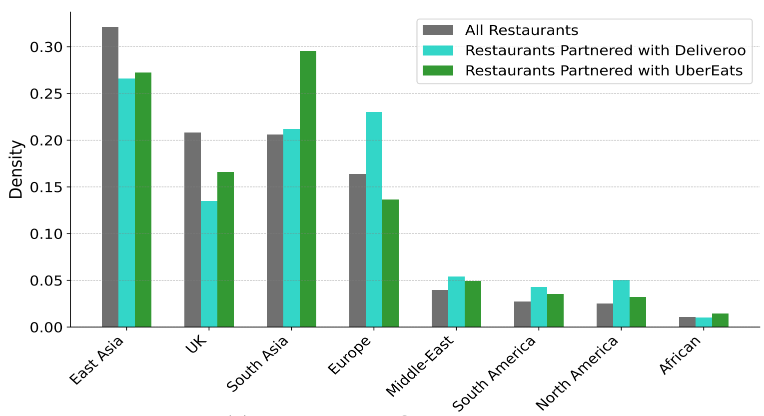
Figure A30. *Notes:* This graph shows the distribution of ethnic groups across the overall economy, the restaurant sector, and managerial positions within the restaurant sector. The data are drawn from the UK Labour Force Survey (2013Q1–2015Q4). The restaurant industry corresponds to SIC code 561, and 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 A31. *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.

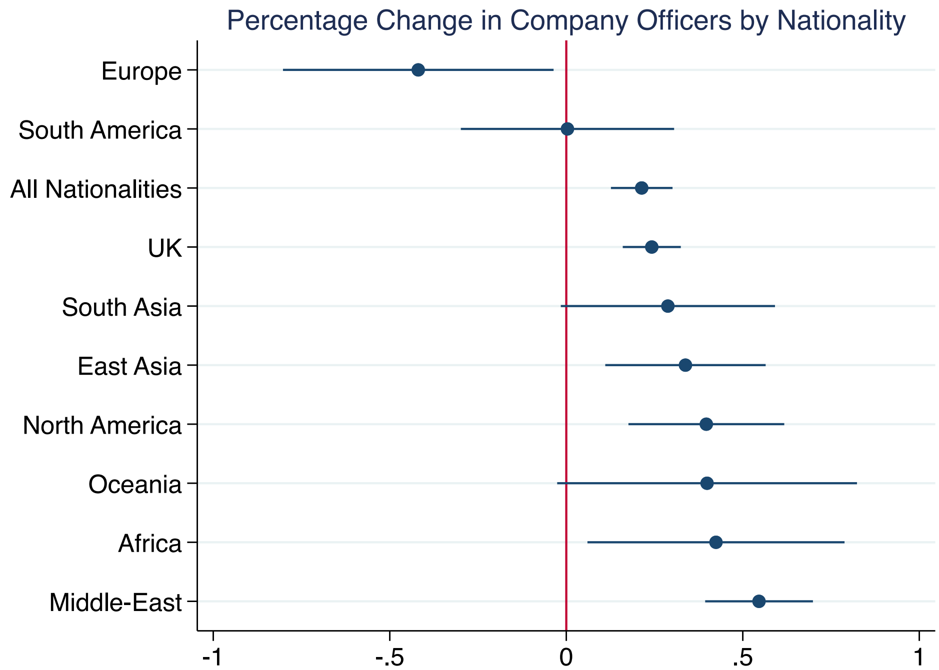


Figure A32. *Notes:* The figure shows the impact of the platform on different entrepreneur nationalities, reported as the percentage changes by computing $\Delta\hat{y}_m = \hat{\beta_m}/E(\hat{y_m}|D_{it} = 1)$, where $E(\hat{y_m}|D_{it} = 1)$ is the average predicted number of entrepreneurs from nationality 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.

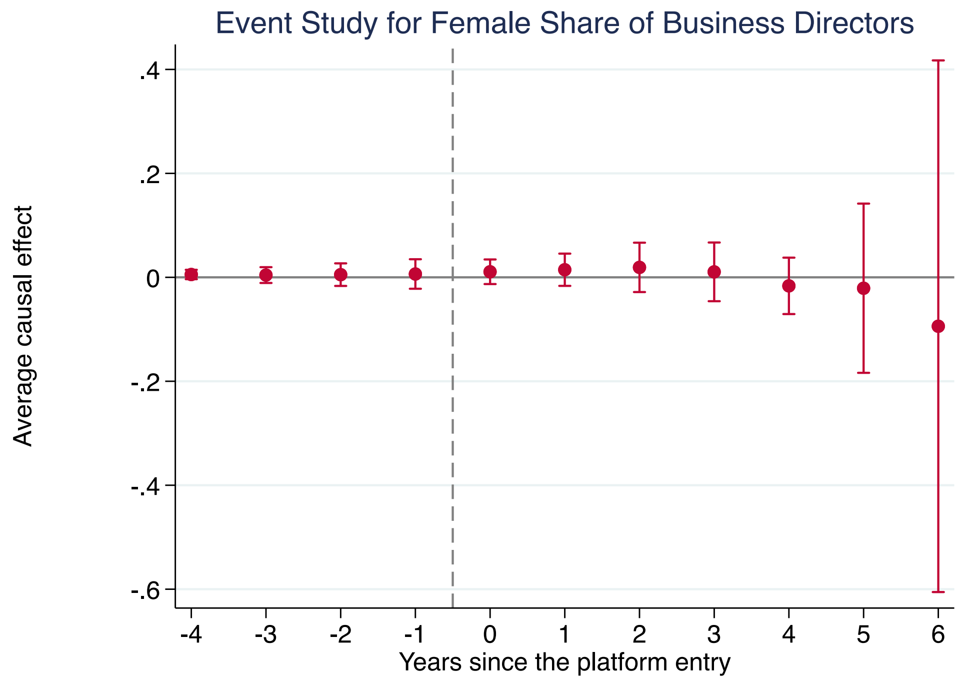


Figure A33. *Notes:* The figure shows the impact of the platform on female share among entrepreneurs. Data is from Company House.

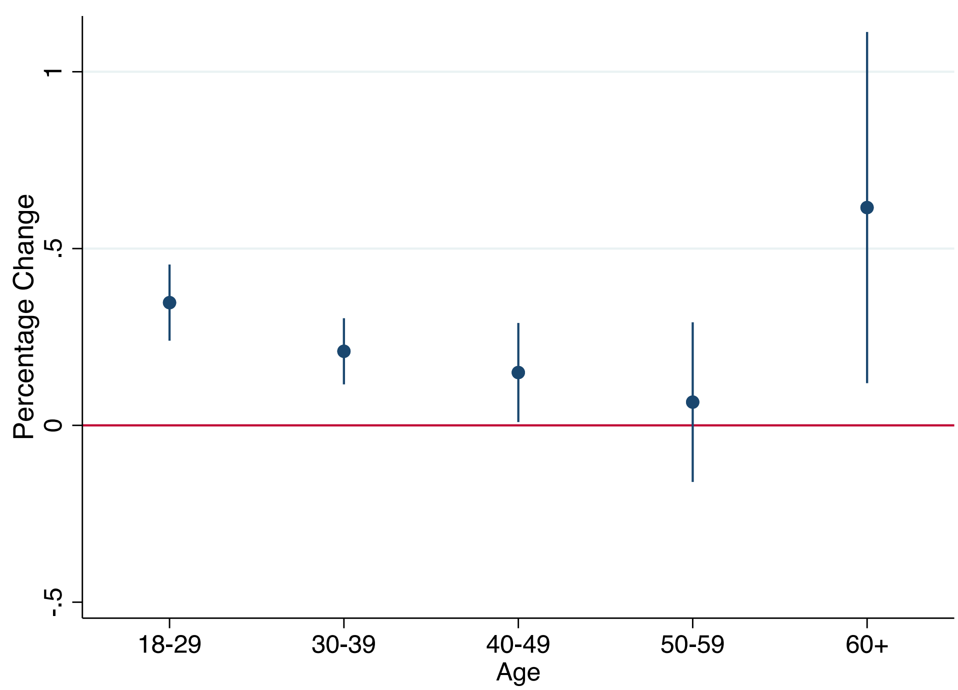


Figure A34. *Notes:* The figure shows the impact of the platform on different age groups in percentage terms. Data is from Company House.

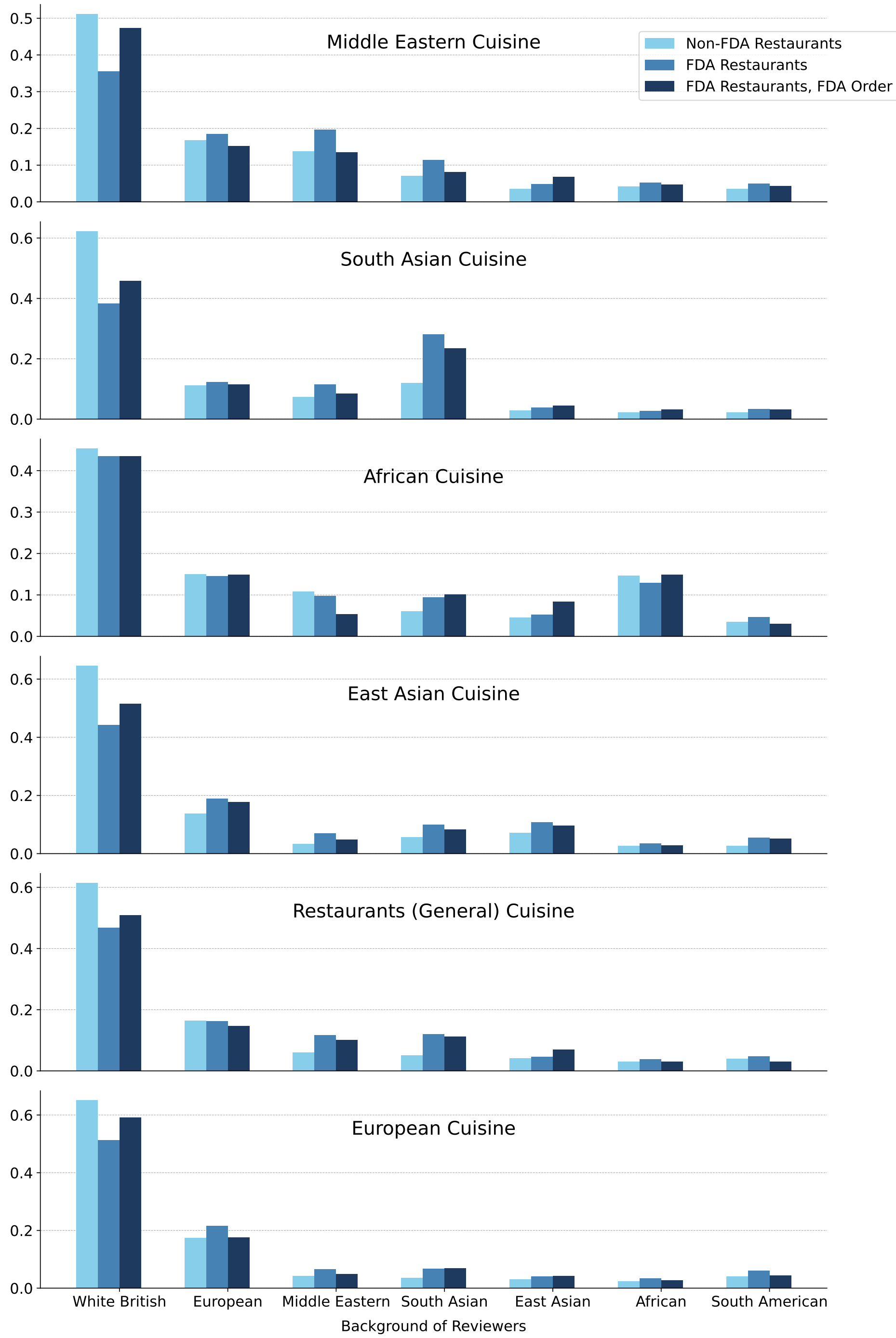


Figure A35. *Notes:* The figure illustrates the distribution of ethnicities of reviewers for different cuisines across three categories: non-FDA restaurants, FDA restaurants, and FDA restaurants with FDA mention. The data is based on restaurants on Google Maps. Cuisine types are categorized as outlined in Table A8. Ethnicities were inferred using a predictive algorithm based on first and last names.

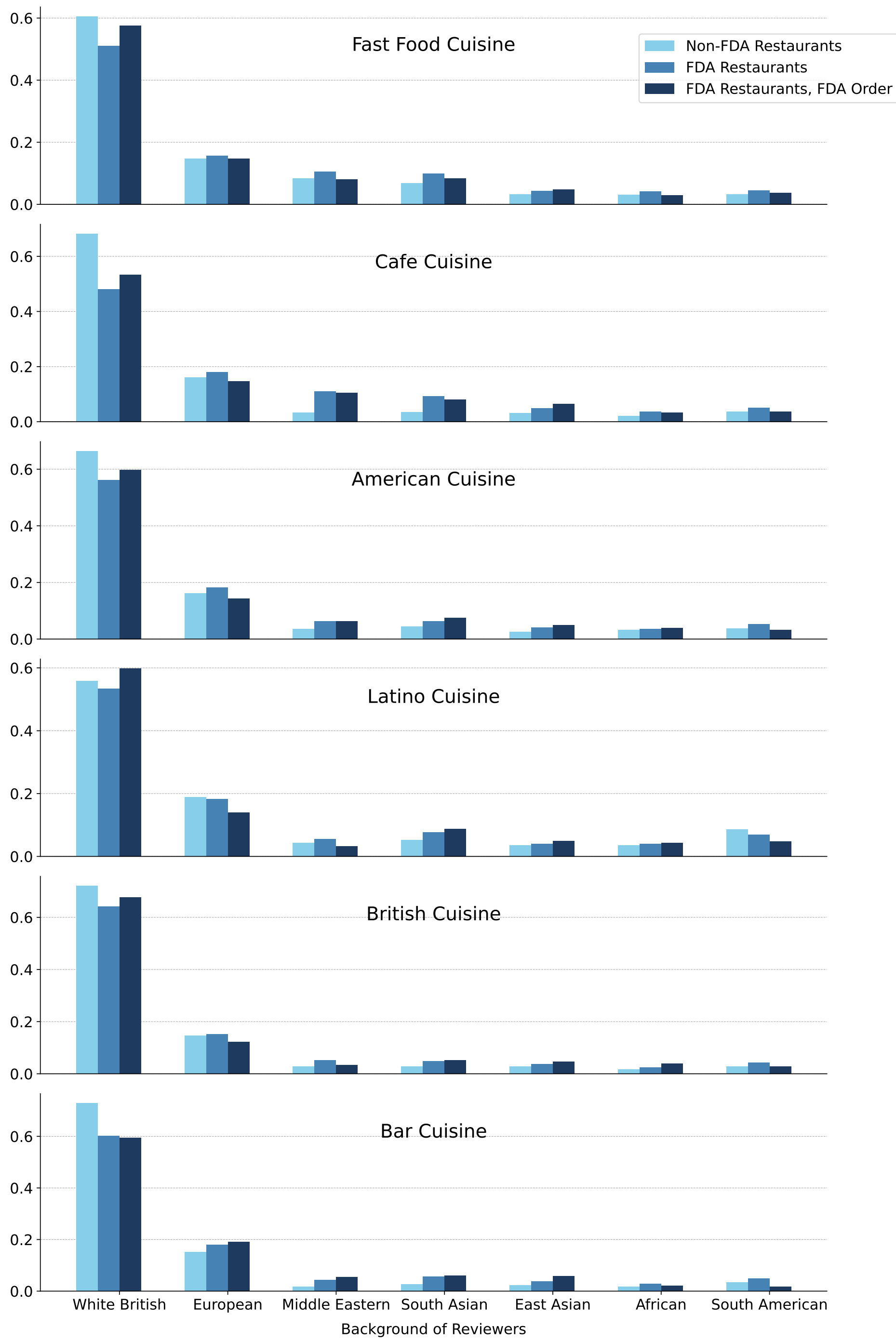
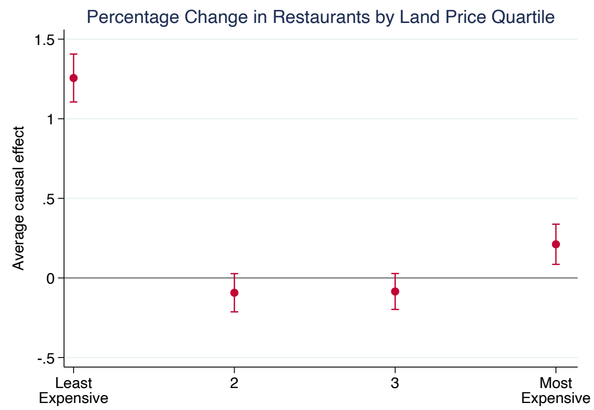
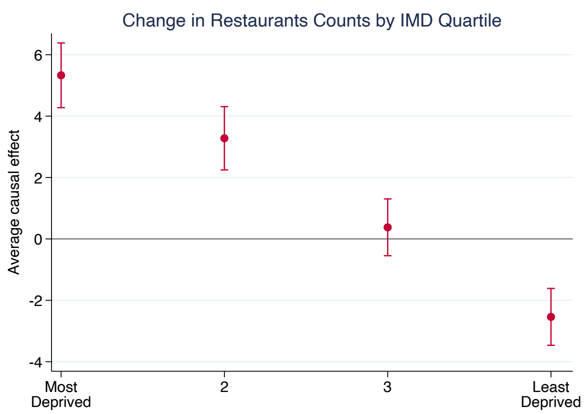


Figure A36. *Notes:* The figure illustrates the continuation of Figure A35, which shows the distribution of ethnicities of reviewers for additional cuisines. The data is sourced from FDA-partnered restaurants.

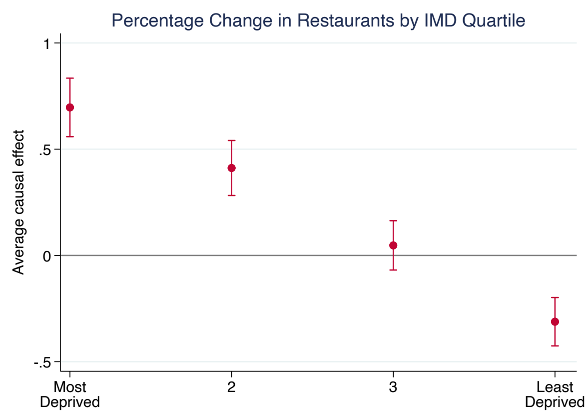
(a) Total Restaurants



(b) Total Restaurant, normalized

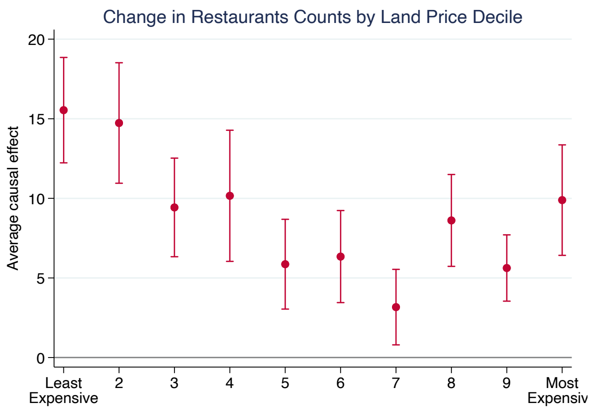


(c) Total Restaurants



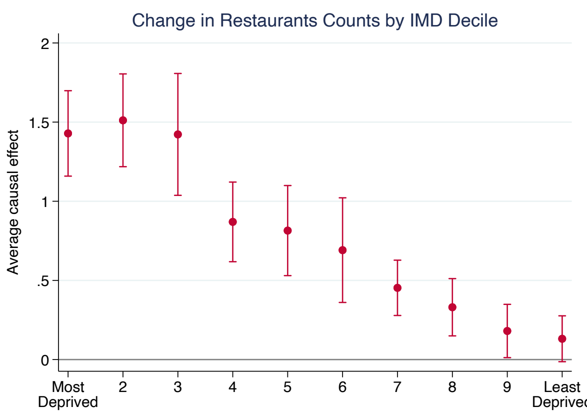
(d) Total Restaurant, normalized

Figure A37. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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 platform rollout on the total number of restaurants segmented by price quartile within postal district as a percentage of the counterfactual outcome, absent food delivery platform (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.

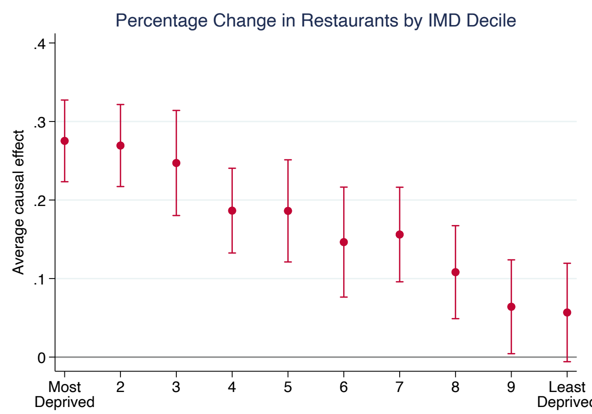


(a) Postal District Price Decile

(b) Postal District Price Decile, normalized



(c) Postal District IMD



(d) Postal District IMD, normalized

Figure A38. *Notes:* Panel (a) presents the average causal effect of food delivery platform 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 platform (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 platform 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.

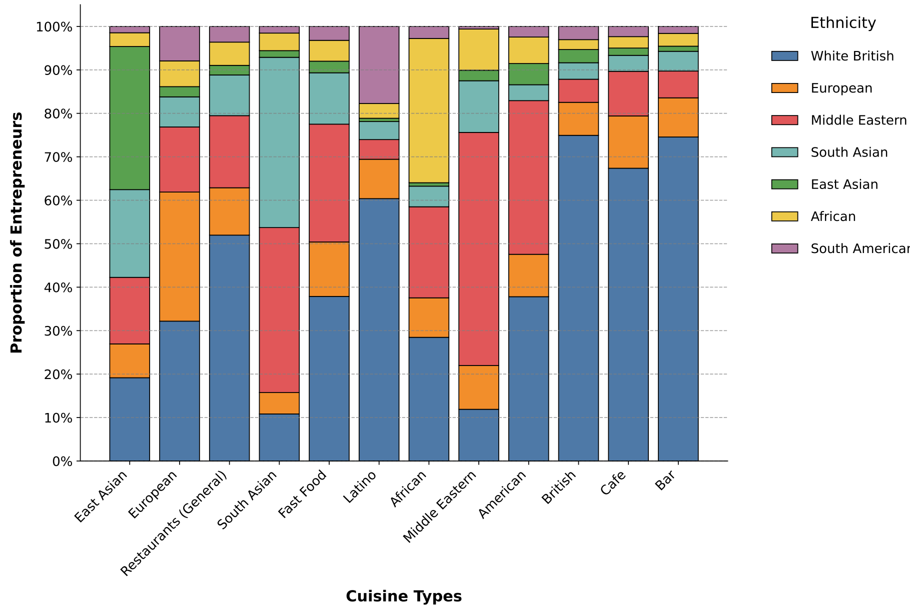


Figure A39. *Notes:* The figure displays the ethnic composition of entrepreneurs across various cuisine types. Cuisine classifications are sourced from Google Maps data, which are then matched with Companies House records containing entrepreneurs' names. As detailed in the text, ethnicity is inferred based on name analysis to estimate the representation of different ethnic backgrounds within each cuisine category..

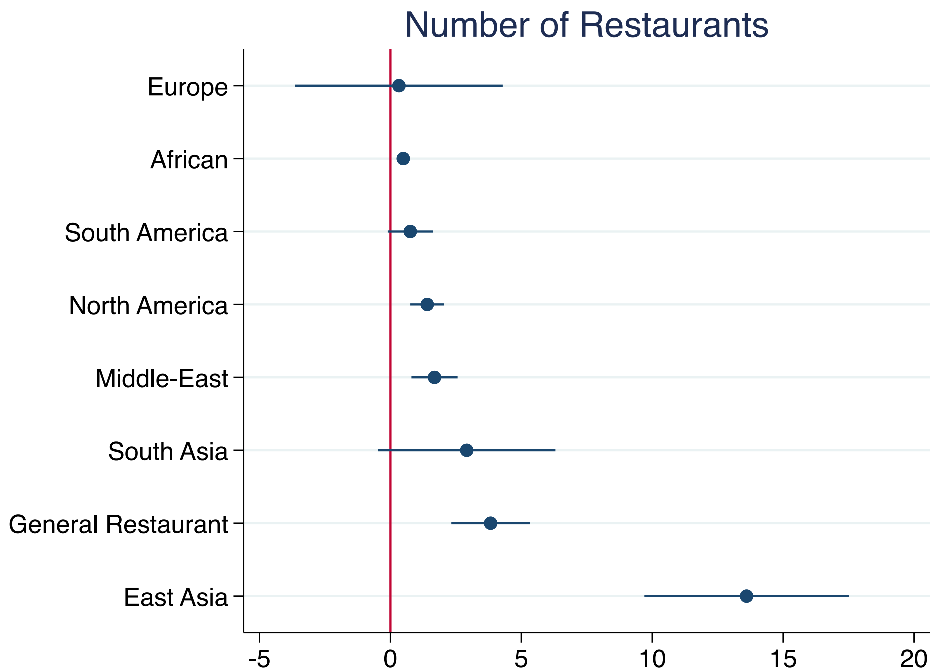


Figure A40. *Notes:* The figure shows the impact of food delivery platforms on the number of restaurants for different cuisine types, indicating changes in the number of establishments across various culinary categories. Cuisine types are categorized as outlined in Table A8. Data is sourced from the Local Data Company (LDC).

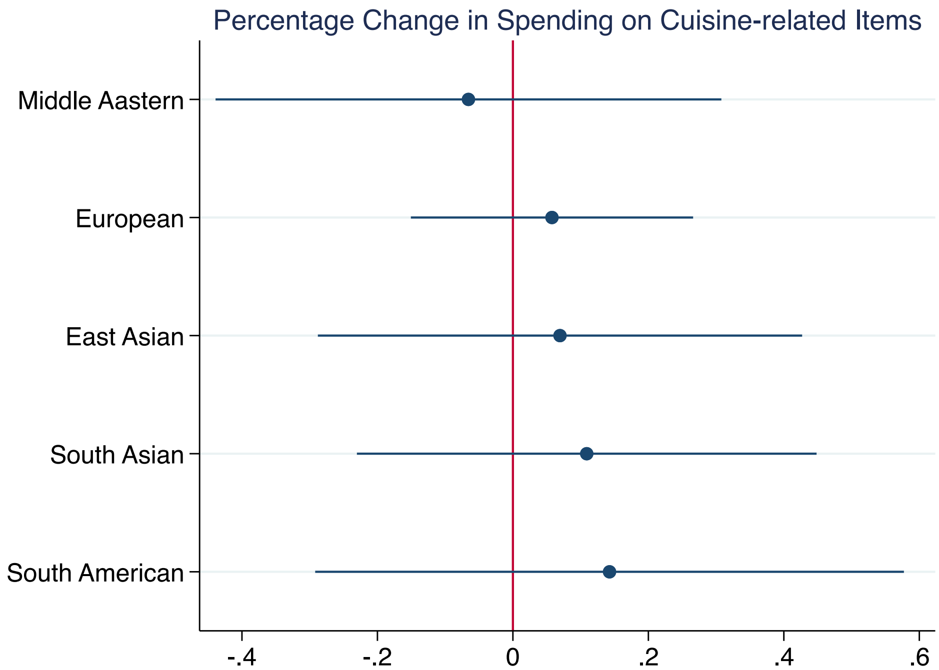


Figure A41. *Notes:* This graph displays the percentage impact of food delivery app rollouts on consumer spending from grocery stores for items representative of specific cuisines, used as placebo tests. The data, sourced from Kantar's Worldpanel Out of Home Panel, and for years 2017 to 2023, includes 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.

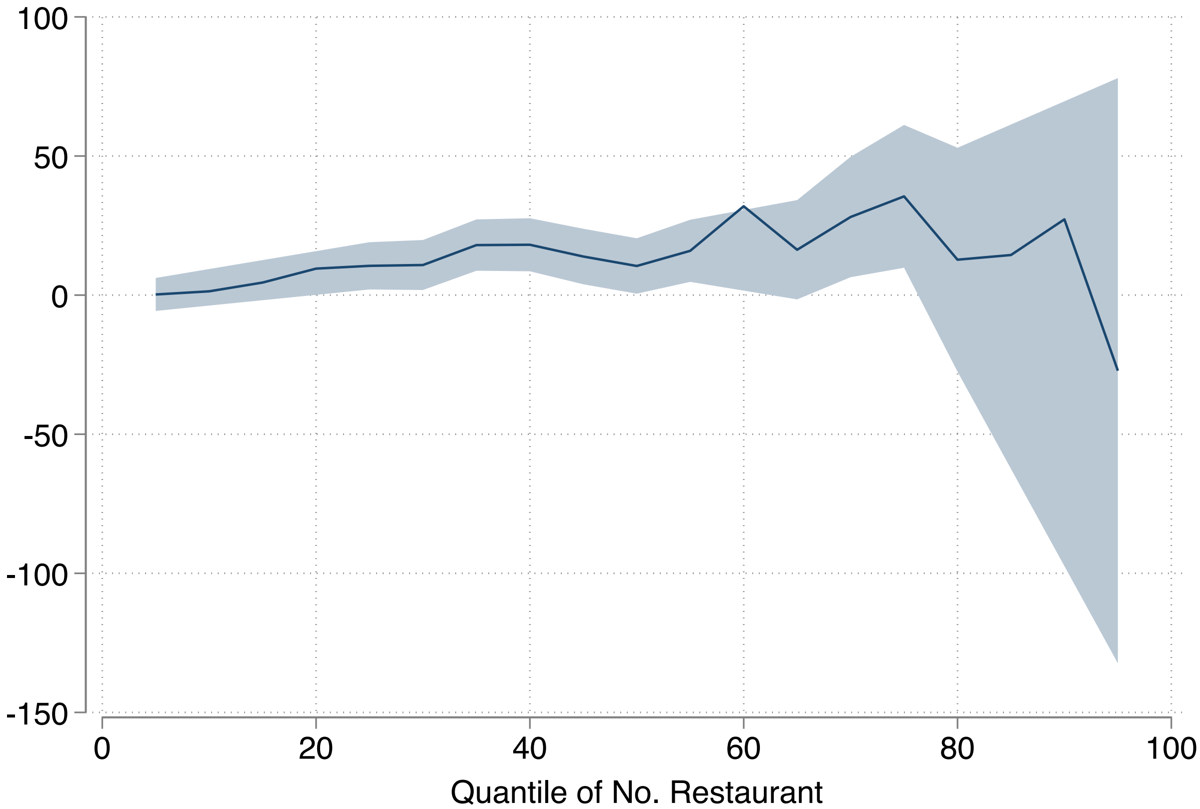


Figure A42. *Notes:* This figure graphs Quantile Treatment Effect (QTE) estimates from the RIF-DiD estimator, including a 90% confidence interval. The outcome variable is the number of restaurants in each local authority and all specifications include postal district and year-fixed effects, as well as local economic indicators and population interacted by time. Data is sourced from the Local Data Company and covers the period from 2010 to 2023.

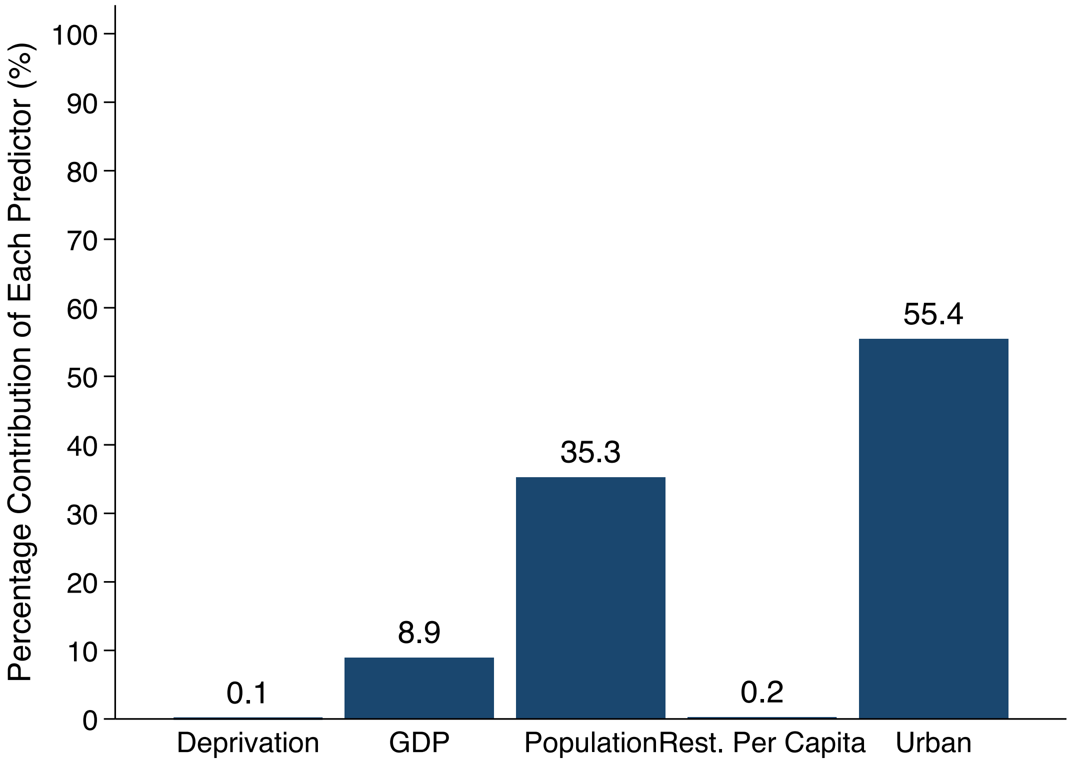


Figure A43. *Notes:* This graph shows the percentage contribution of each predictor to the R-squared value of the regression model assessing the impact of various factors on the rollout dates of food delivery platforms in different postal districts. Predictors were selected using the Best Subsets Selection (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. FDA 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 A8. 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 each dataset. 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-owned		-0.14	-0.16
		(0.01)	(0.01)
Minority × 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." FDA 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

	FDA 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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