Arndt-Corden Department of Economics

Crawford School of Public Policy

ANU College of Law, Governance and Policy

Food one click away: The impact of online food delivery platforms on food security in Indonesia

Pyan A. Muchtar

and

Budy P. Resosudarmo*

Arndt-Corden Department of Economic
Crawford School of Public Policy
Australian National University

* Corresponding author: budy.resosudarmo@anu.edu.au

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Abstract

This paper examines the causal effects of online food delivery (OFD) platforms on household food security in the context of a developing country, Indonesia. We construct food security data from households' consumption surveys from 2012 to 2022 and merged it with a novel dataset on OFD platform penetration across districts, compiled through a combination of internet scraping and machine learning. Utilizing a contemporary event-study estimator to analyze the impact, our findings indicate that the expansion of OFD services enhances food security at the district level, with a more pronounced effect in rural areas, among younger households, and male-led households. We also show that this impact is likely driven by increased competition in the food market.

Keywords: Indonesia, online food delivery, food security

JEL Classification: D12, O14, O33

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1. Introduction

Over the last decade, advancements in digital technology have significantly altered how consumers approach food consumption (Granheim et al., 2022; Sarmiento & Kim, 2021). With the rise of the sharing economy and digital payment system, Online Food Delivery (OFD) platforms have been expanding across the globe and become a popular choice for food purchasing. Statista Market Insight reported that the user penetration increased from 9.3% in 2017 to 24.7% in 2023 with revenue of 0.39 trillion USD. These platforms provide some advantages for all parties involved, including consumers, couriers, food vendors, and the platform itself (He et al., 2019). They offer convenience for consumers with a wide array of food choices that can be delivered directly to their doorsteps with just a click. They also transform the food market, allowing restaurants to access a new revenue stream while maintaining input efficiency.

The presence of OFD platforms comes with a possible advantage in addressing food security concerns, particularly in developing countries where access to adequate dietary energy remains a challenge. On the demand side, people may benefit from the wealth effect of OFD, obtaining higher capacity in purchasing adequate food. Li et al. (2021) found that Uber's penetration boosts labor force participation, lowers the unemployment rate among residents living in poverty, and enhances the employment and economic conditions of low-income employees. Furthermore, Uber's presence leads to a reduction in the number of traditional low-skill and/or low-wage jobs, while simultaneously increasing the wages associated with these positions. Koling et al. (2024) documented that Uber and Lyft entry caused an increase in employment, earnings, and gross domestic product.

On the supply side, OFD may leverage technological resources to induce competitiveness in the food market, potentially making food more accessible and affordable. Reshef (2023) documented an increase in the number of restaurants when Grubhub was introduced. Li and Wang (forthcoming) found OFD boosts overall takeout sales for restaurants and also generates beneficial spillovers, increasing customer visits for dining in. Moreover, some studies highlight the issues of food insecurity coming from the supply side (Dupont & Thirlwell, 2009; Warr, 2014), particularly in the distribution system (George & McKay, 2019; Mohan et al., 2013) in which OFD can play some roles. For instance, found that OFD contributes to the resilience of the urban food system in China when faced with the external shock of COVID-19.

While the meal distribution industry has advanced significantly with the expansion of online food delivery (OFD) platforms, a contrasting trend emerges in the realm of food security. Economic reports indicate that food security remains a pressing challenge, particularly in developing countries (Dupont & Thirlwell, 2009; Warr, 2014). The 2023 Global Hunger Index stands at 18.3, reflecting a marginal decline from 19.1 in 2015.

Moreover, the proportion of undernourished people globally increased from 7.5 percent in 2017 to 9.2 percent in 2022. This apparent contradiction raises a critical question: How has the proliferation of OFD platforms influenced household food security?
This paper seeks to address this question by examining the causal impact of OFD platform proliferation on household food security in Indonesia. Indonesia represents a particularly relevant case for this study. As a rapidly developing Southeast Asian country with fast-growing internet penetration, it offers a unique context to explore the role of OFD platforms in food security.

Since 2015, online ride-hailing companies expanded into the food delivery sector in Indonesia[1]. They implemented aggressive marketing and diverse restaurant partnerships to boost their growth. According to Rakuten Insight, the annual revenue of Indonesia's OFD market is 12.2 million U.S. dollars in 2022. The market is dominated by two big players, Grab and Go-jek. In 2022, these players had a gross merchandise value (GMV) share of 49 and 44 percent of the total GMV of 4.5 billion U.S. dollars, respectively. Despite experiencing one of the fastest economic growth rates in the region, food security remains a persistent challenge (Amrullah et al., 2019; Ardianti et al., 2023). According to the Global Food Security Index by the Economist Intelligence Unit, Indonesia ranked 63rd out of 113 countries in 2022. Similarly, the Global Hunger Index ranked Indonesia 77th out of 125 countries in 2020. Furthermore, since 2015, Indonesia has experienced significant growth in the adoption of OFD platforms, with current estimates indicating that over 30 million individuals actively use these services.

We combine data from national survey with a novel dataset on OFD platform expansion, constructed using semi-manual web scraping and machine learning predictions. Utilizing aggregated district-level data, our analysis focuses on an intention-to-treat (ITT) impact evaluation approach. Exploiting the staggered nature of the OFD penetration, we utilize an event-study estimator developed by Sun and Abraham (2021) to evaluate the impact.

We found evidence that OFD penetration leads to an increase in households' food security at overall impact of 3.7 percentage point. This effect is robust across different calorie thresholds, alternative outcomes, and alternative estimators. Some evidence to support the identifying assumption of causal effect is provided, including the parallel trend assumption and no anticipation. We then show that the OFD entry increases both household spending and calorie intake. To partially check that the increase comes from OFD, we reconstruct both outcomes by only considering consumption on ready meals and the result remain the same.

In addition, we found heterogenous effect across different location and household characteristics. The improvement of food security due to OFD entry is more substantial in rural districts and outside Java Island. The effect is also more prominent among

[1] Gojek became the first mover that introduced GoFood. Subsequently, Grab expanded its horizons to include GrabFood in 2016. Uber Eats, with its global recognition, and Shopee Food, an extension of the Shopee e-commerce platform, both sought to capture a slice of the burgeoning market. While Uber Eats faced challenges and eventually exited some markets in Southeast Asia, Shopee Food capitalized on its existing e-commerce user base to make significant strides.

younger households, and male-led households. We provide suggestive evidence that this impact is likely driven by increased competition in the food market rather than wealth improvement. Furthermore, we provide household-level analysis by using phone survey data during the COVID-19 period. Using linear regression, we result show that the OFD utilization is significantly associated with better food security, after controlling for income and other individual covariates.

This paper contributes to three strands of literature. Firstly, our paper adds to studies regarding the disruption of online technology in society. While many studies cover topics like the effect of ride-hailing apps on pollution (Sarmiento & Kim, 2021), labor productivity (Shotaro Nakamura, 2024), and gender gap (Cook et al., 2021), we focus specifically on OFD service and its implication on food security, which is underexplored. We also add to some empirical studies showing how food security is affected by technology like the internet (Ankrah Twumasi et al., 2021; Ardianti et al., 2023).

Secondly, we contribute to the growing literature on the impact of food delivery services. Recent studies have explored the association between food delivery platforms and sustainability (Li et al., 2020), domestic food preparation (Babar et al., 2021), and eating out behavior (Safira & Chikaraishi, 2022). While these studies report descriptive evidence with limited correlational relationships, we aim to elucidate causal inference. We also extend the discussion on the nutritional quality of food sourced through OFD platforms. For instance, Mahawar et al. (2022) and Wang et al. (2021) investigate the nutritional quality of restaurant menus listed on OFD platforms in New Zealand and Australia, respectively, using survey data. However, their focus is on the supply side by analyzing menu offerings. In contrast, our paper adopts a demand-side perspective, drawing on household survey data to examine consumer behavior. Furthermore, we provide new insights by situating our analysis within the context of a developing country.

Finally, our paper adds to a growing literature in development economics that uses machine learning to improve identification strategy, particularly in addressing measurement errors in treatment assignments. In our paper, we use machine learning to predict the entry timing of OFD in less populated areas which are prone to error in treatment assignment due to limited media coverage.

The remainder of the paper proceeds as follows. Section 2 describes the data construction. Section 3 explains the empirical strategy as well as its identifying assumption. In Section 4, we present a set of results, followed by robustness checks and some extended analysis, including heterogeneity, mechanism, and discussion on COVID-19 period. Section 5 concludes.

2. Data

Our primary dataset is derived from the National Socio-economic Survey (Susenas) which is conducted annually by Statistics Indonesia (BPS). Susenas offers a nationally representative sample of approximately 350,000 households each year. To facilitate our study, we aggregate individual household data to obtain district-level observations, yielding data from 514 distinct districts throughout 2012 to 2022[2]. For the aggregation, we use the frequency weight as provided in the dataset. We gather information about the infiltration of OFDs across districts in Indonesia using semi-manual internet scraping from news, blogs, and social media. Both datasets are merged using year and district identification.

2.1. OFD Penetration

For our study's context, districts that experienced at least one OFD infiltration form our "treatment" group, whereas unpenetrated districts serve as the control group. Once a district is treated, it remains treated until the end of the observation period. In defining the treatment, we consider two main players in the OFD market, which are Gojek and Grab because the coverage of other small OFD platforms is a subset of the big two. We constructed a unique dataset chronicling the OFD platform roll-out across districts. The delineation was based on service location indicators on the official Gojek and Grab websites. Regrettably, these platforms do not disclose the operational commencement dates in the penetrated districts.

We adopted the following strategy to obtain the timing of OFD penetration across districts. Firstly, theWayback Machine[3] was used to trace the initial mentions of districts on these platforms' official websites, though this method only dates back to 2019. To obtain the data in earlier years, we turned to manual web scraping. By searching for news and blogs that chronicled the introduction of OFD platforms in specific districts, we could deduce approximate timelines from the publication date. We utilize keywords like ”Gojek entered city A in...”. Additionally, district-specific Facebook communities and Instagram accounts were another reservoir of information. Searches such as ”Gojek community in city A" led us to group establishment dates on the respective pages or accounts. This meticulous process was iteratively applied across all districts.

However, the treatment assignment with this procedure may be prone to measurement error due to the reliability issue of the sources. While we can find valid national media coverage for Java and Sumatra, which are populated by more than 75% of the total population, districts outside the two islands are often neglected by mainstream media, forcing us to use local media or personal blogs which may not be fully reliable and thus possibly cause measurement error. To address this issue, we exploit machine learning (ML) to predict the timing penetration of OFD in districts outside Java. We utilize several ML function classes, including Penalised Logistic Regression, K-Nearest Neighbor, Support Vector Machine, and Random Forest. The features used to predict the penetration are dozens of socio-economic variables. We first train these models using 80% random sample data from Java and Sumatra. We test the validity of these models

[2] Some districts experienced administrative splits before 2016. To uphold the consistency, we created pseudo-districts for the newly formed districts. These pseudo-districts inherited their parent district's values for all variables in the periods before their formal establishment. Essentially, we replicated parent district data to represent child districts that hadn't materialized prior to their respective splits.

[3] The Wayback Machine serves as a digital repository of the World Wide Web and is an initiative by the Internet Archive, a San Francisco-based nonprofit organization. Established in 1996 and made accessible to the public in 2001, this tool enables users to journey ”back in time” to view previous versions of websites. See https://archive.org/web/

with the held-off set data (the rest 20%) and found that Random Forest has the best performance with 97% accuracy and 95% f1-score (as shown in Table A.1). We then use all observations in Java and Sumatra as training data and predict the treatment status of districts outside Java and Sumatra.

Table 1. OFD penetration across different methods

Year	New penetrated districts		
	Scraping	ML prediction	Combination
2015	27	26	27
2016	7	2	7
2017	101	119	117
2018	57	52	55
2019	18	14	16
2020	7	3	3
2021	2	2	0
2022	5	5	4

Source: authors' calculations

Table 1 shows the OFD platform's expansion each year across treatment assignment methods. The number of treated districts across years shown by ML prediction is slightly different from that of original data from online scraping. Assuming measurement error outside Java and Sumatra exists, the ML prediction improves the treatment assignment. Moving forward, we decided to use the combination technique, which means we assign treatment based on the earliest OFD penetration either from online scrapping or ML prediction. With such a treatment assignment, our impact estimation would be the most conservative.

As of 2022, our dataset classified 239 districts as treated and the residual 275 as nontreated. The spread of the penetration is presented in Figure 1. The rollout began in 2015, predominantly targeting metropolitan hubs like Jakarta, Bandung, and Surabaya. The subsequent years saw the service proliferating to other major cities and eventually trickling down to smaller districts. As clearly shown, the distribution is not random - concentrated in big cities, particularly in Java Island. Nevertheless, our identification strategy does not rely on the randomness/exogeneity of the shock.

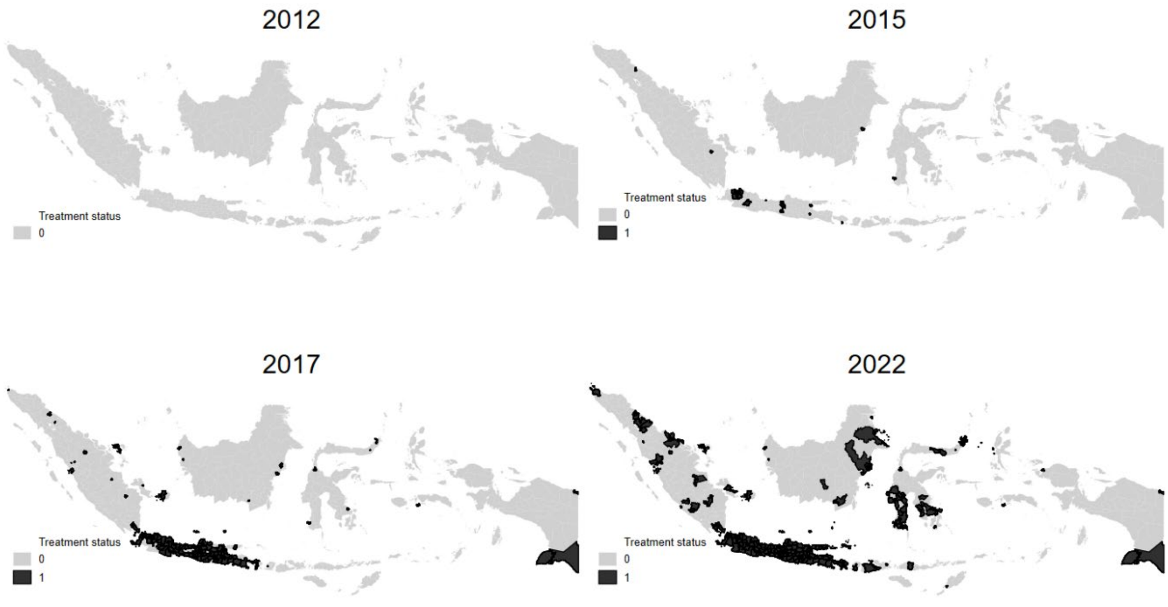


Figure 1. Districts penetrated by OFD across years

Furthermore, it is worth noting that our main estimation does not focus on analyzing the individual impact as we are unable to identify individual users of OFD in our dataset. Once an OFD service penetrates a district, we assume that everyone in the respective district is affected. Therefore, our analysis is limited to the intention-to-treat (ITT) impact evaluation at the district level.

2.2. Outcome Variables

The primary outcome variable that we focus on is food insecurity, constructed from the household nutritional intake. The data are sourced from the consumption module of Susenas which asks households to specify family consumption and individual consumption, categorized into different period-based classifications (e.g. weekly or monthly) and different types of food (e.g. rice, oil, meat, etc.). The measure includes price, quantity, and nutrition. The food consumption is labeled as either food prepared at home (FAH) or food away from home (FAFH). Unfortunately, the data does not allow us to distinguish food ordered from OFD from the bulk share of FAFH. We sum all consumption from all household members, adjust the period, and divide it by household size so we can obtain daily per capita consumption. We exclude consumption of alcohol and tobacco products.

As the treatment is at the district level, we construct our outcome variables at the district level as well. The primary outcome is districts' food security, an aggregation variable specifying a percentage of people in the respective district whose daily consumption is above a certain threshold, which is the minimum energy requirement for daily activity. The value ranges between 0% (insecure) to 100% (secure). In the main analysis, we use standard threshold of 2100 kcal, as suggested by the Ministry of Health. For sensitivity check, we also construct food security with different threshold at 2,000 kcal 2,200 kacl.

Figure 2 shows the average food security across treated and never treated group using 2,100 kcal threshold.

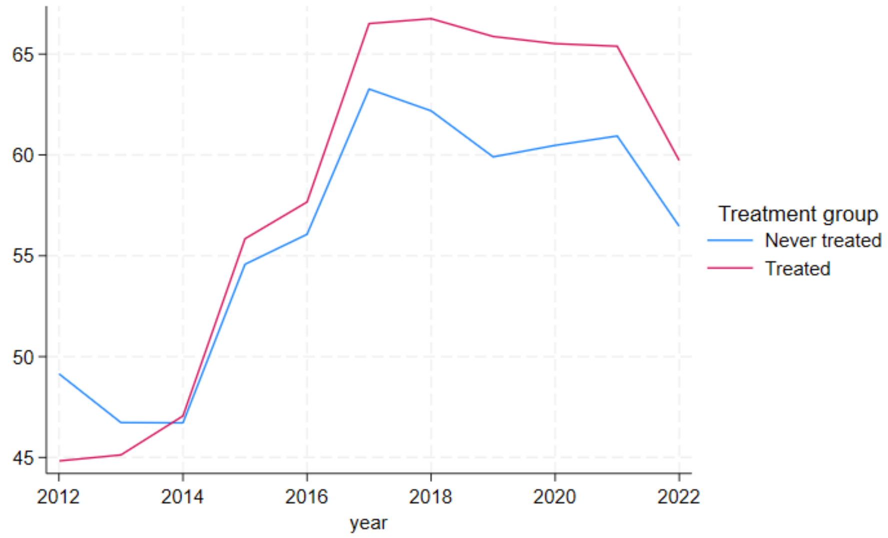


Figure 2. Food security trend across treatment group

We also use other primary outcome variables like food expenditure and calorie intake. Food expenditure is represented as monthly per capita expenses and, for interpretative ease and to counteract data skewness, we log-transform this variable. Nutritional intake is gauged by per capita daily calorie consumption, enumerated in kcal. We further decompose this intake into its constituents: protein, carbohydrate, and fat, each measured in grams.

2.3. Covariates

We employ some covariates, including population density (ln), highschool participation rate, vehicle ownership rate, and internet access rate. These variables are obtained from either Susenas aggregation data or Regional Information System (Simreg) data from the National Planning Agency (Bappenas). The mean trend across treatment groups of these covariates is presented in Figure A.1. We chose these covariates because they are related to the OFD penetration and potentially cause the outcome moves differently between treatment and control group. We wish to part out their effects in the estimation.

The summary statistics of variables used in this paper is presented in Table 2. Observations are in district level. During our study periods, 2012 – 2022, the mean of food security with 2,100 kcal threshold is 57.03% with an average per capita calorie intake of 2,332 kcal.

Table 2. Summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Food security (2,000 kcal)	5,653	63.54%	15.34%	2.54%	100.00%
Food security (2,100 kcal)	5,653	57.03%	15.69%	1.66%	99.91%
Food security (2,200 kcal)	5,653	50.63%	15.55%	0.62%	97.86%
Monthly pcp food expenditure (Rp)	5,653	491,542	162,942	124,295	2,127,595

Daily pcp calorie intake	5,653	2,332	244	1,366	3,491
Internet access	5,616	28.57%	19.35%	0.01%	83.19%
Population density	5,653	1089.25	2613.17	0.56	21346.41
High school participation rate	5,653	93.72%	7.19%	13.07%	100.00%
Vehicle ownership rate	5,653	69.52%	21.02%	0.00%	97.39%
Monthly pcp GDRP (thousand Rp)	5,631	47,361	52,617	521	499,325
Unemployment rate	5,645	8.65%	3.74%	0.04%	47.37%

Source: Authors' calculations based on Susenas and Simreg.

3. Method

3.1. Identification strategy

To examine the impact of OFD on food security, we employ a Difference-in-Difference (DiD), in which the OFD penetration is considered as the "treatment". Given the staggered nature of the penetration, we specifically use modern event study approach developed by Sun and Abraham (2021), henceforth called SA. The parameter that we want to estimate is the average treatment effect on the treated (ATT), although we can only claim the effect as ITT as explained in the previous subsection. Furthermore, it is important to note that, for the context of staggered treatment in this study, the use of two-way fixed effect (TWFE) yields a biased estimate due to a negative weight issue (also commonly known as a 'forbidden comparison') (Borusyak et al., 2024). SA estimator eliminates such an issue by interacting relative period indicators with cohort indicators. While there are other event study designs that also address such a problem, we utilize SA for some reasons. SA allows for specification with never-treated controls and the inclusion of time-varying covariates. It can perform on unbalanced panel data yet is still able to capture fixed effects. Additionally, it allows for specifying the relevant periods before and after the treatment. The SA specification is as follows.

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{e \notin C} \sum_{l \neq -1} \delta_{e,\ell} \cdot \mathbb{I}\{E_i = e\} \cdot D_{i,t}^{\ell} + \epsilon_{i,t} \quad (1)$$

Let $Y_{i,t}$ represent the outcome for entity i during period t and let E_i denote when entity i first encounters a binary, permanent treatment. The terms α_i and λ_t are fixed effects for the entity and time, respectively. We represent $D_{i,t}^{\ell} := \mathbb{I}\{t - E_i = e\}$ indicating that entity i is ℓ time intervals distant from the initial treatment during the specific time t. Thus, $\mathbb{I}\{E_i = e\} \cdot D_{i,t}^{\ell}$ is a cohort-specific relative time indicator. For entities that never undergo treatment (where $E_i = \infty$), we designate $D_{i,t}^{\ell} = 0$ across all values of ℓ and t. The coefficient $\delta_{e,\ell}$ obtained from regression acts as an event study estimate for the average effect of treatment on the treated cohort (CATT), given specific pre-periods and control cohorts[4].

[4] The causal parameter for the difference in difference method or event study is normally average treatment on the treated (ATT) but we only aim for the ITT given the nature of our treatment data as previously explained

To form the SA estimator, we take a weighted average of estimates $\hat{\delta}_{e,\ell}$ for $CATT_{e,\ell}$ from Equation (1) with weight estimates of sample cohort share, The SA estimator is formally specified as:

$$\hat{v}_g = \frac{1}{|g|}\sum_{\ell \in g}\sum_{e} \hat{\delta}_{e,\ell}\, Pr\{E_i = e | E_i \in [-\ell, T - \ell]\} \tag{2}$$

We run this procedure using Stata package of *eventstudyinteract*. In our analysis, we incorporate four leads and five lags (including $\ell = 0$). The baseline is one year before the treatment ($\ell = -1$). Note that the first treatment occurred in 2015 and the data span from 2012 to 2023, we utilize 4-year leads and 5-year lags. Furthermore, we set the control cohort to be never-treated units $C = \{\infty\}$.

3.2. Identifying assumptions

As previously mentioned, our estimation does not depend on the exogeneity of the OFD penetration timing. Similar to DiD estimators, the validity of SA depends on two core assumptions: parallel trends in baseline outcomes and no anticipation behavior prior to treatment, as outlined by Sun and Abraham (2021). When these criteria are met, the treatment impacts are deemed to have causality.

The parallel trend suggests that, if not for the treatment, the outcome would follow a similar trajectory in both the control and treatment groups before and after the treatment. Our *ex-ante* support for parallel trend is shown in Figure 2. The mean of district food security between treatment groups and control groups follows the same trajectory before 2017, except 2012, when the majority of districts are not yet penetrated. To formally test the parallel trend, we will later show that the dynamic effect of OFD on the periods before the treatment are not statistically significant. In addition, we check the robustness of the parallel trend using two approaches developed by Roth (2022) and Rambachan and Roth (2023).

The no anticipation asserts that the treatment has no impact during the pre-treatment phase. To formally test this, we run a falsification test in which the period of OFD penetration is shifted one year prior to the actual penetration. If there is no significant effect in the year of falsified penetration, then district food security does not depend on future OFD penetration.

4. Result

4.1. Main Result

4.1.1. The effect of OFD platforms on food security

We run equation 1 and use the underlying $CATT_{e,\ell}$ estimate ($\hat{\delta}_{e,\ell}$) to calculate $\hat{v}_g$ as in Equation 2. The outcome is districts' food security, the percentage of people in the district who have sufficient food consumption, with different calorie intake thresholds across columns. Table 2 presents the estimation results, $\hat{v}_g$, both without and with covariates. We utilize district-fixed effect and year-fixed effect in all specifications. On the estimation without covariates, regardless of the threshold, we found an increase in districts' food security due to the proliferation of OFD with overall treatment effects around 3.4 percentage points (henceforth, pp) - 3.8 pp, depending on the cut-off for defining food security, statistically significant at 0.1% level. In the period of penetration (lag0), treated districts experienced 2.3 pp - 2.7 pp increase in food security and the effect gets slightly larger in the subsequent periods. These periodical treatment effects are also significant at 0.1%level.

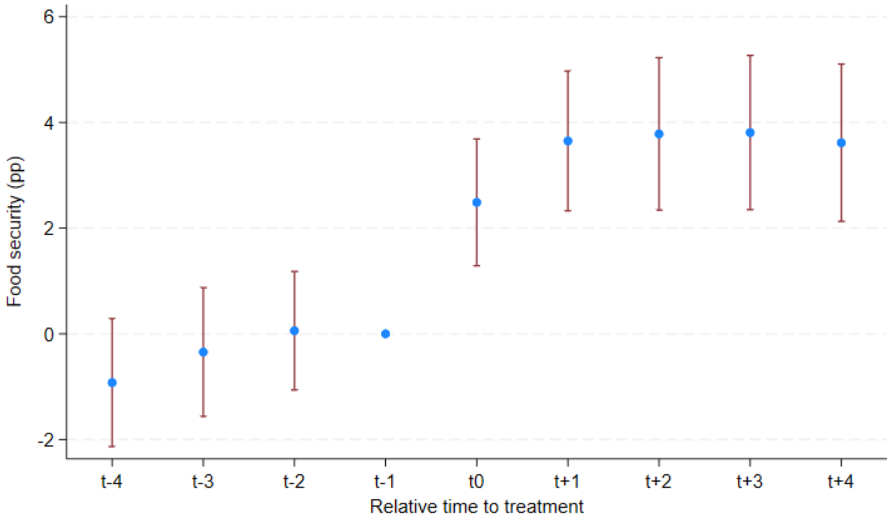
Table 3. The effect of OFD platforms on food security

	Dep var: food security					
	Unconditional on covariates			Conditional on covariates		
	2,000 kcal	2,100 kcal	2,200 kcal	2,000 kcal	2,100 kcal	2,200 kcal
T – 4	-0.715	-0.576	-0.439	-0.707	-0.592	-0.459
	(0.605)	(0.592)	(0.580)	(0.607)	(0.595)	(0.582)
T – 3	-0.355	-0.328	-0.233	-0.377	-0.367	-0.286
	(0.589)	(0.584)	(0.568)	(0.597)	(0.593)	(0.578)
T – 2	0.212	0.252	0.093	0.114	0.145	-0.019
	(0.542)	(0.551)	(0.545)	(0.538)	(0.549)	(0.544)
T = 0	2.297***	2.571***	2.702***	2.248***	2.525***	2.658***
	(0.579)	(0.609)	(0.635)	(0.579)	(0.608)	(0.634)
T + 1	3.470***	3.817***	3.956***	3.480***	3.833***	3.980***
	(0.638)	(0.671)	(0.694)	(0.642)	(0.675)	(0.696)
T + 2	3.823***	4.102***	4.136***	3.835***	4.118***	4.160***
	(0.702)	(0.737)	(0.757)	(0.708)	(0.742)	(0.762)
T + 3	3.746***	4.197***	4.248***	3.713***	4.164***	4.235***
	(0.712)	(0.747)	(0.756)	(0.719)	(0.754)	(0.762)
T + 4	3.722***	4.023***	4.007***	3.724***	4.037***	4.032***
	(0.721)	(0.760)	(0.774)	(0.728)	(0.767)	(0.780)
Overall ATT	3.412***	3.742***	3.810***	3.40***	3.735***	3.813***
	(0.541)	(0.568)	(0.583)	(0.546)	(0.572)	(0.586)
Joint pre-trends test						
Prob > chi2	0.811	0.706	0.878	0.672	0.743	0.885
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	No	Yes	Yes	Yes
N districts	514	514	514	514	514	514
N observations	5653	5653	5653	5630	5630	5630

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels.

Our preferred specification is the estimation with the 2,100-kcal threshold. In other words, the expansion of OFD services increases the level of food security by approximately 2.7 percentage points.

The graphical representation of the event study is shown in Figure 3. The individual and joint pre-trends in all specifications are statistically insignificant, providing support to our parallel trends. assumption and hence causality. More rigorous tests on the parallel trend assumption will be presented later. Note that the parallel trend is satisfied without incorporating covariates, our ITT effect is not conditional on certain variables that potentially evolve differently across treatment and control groups over years. In the last three columns, we introduce some socio-economic covariates, including GDRP per capita, population density, population density (ln), high-school participation rate, vehicle ownership rate, and internet access rate. We condition these observables as we suspect that covariate-specific time trends are modifying the value of food security. If the inter-temporal path of food security depends on either income or population density, conditioning the parallel trends on these covariates is potentially better. Reassuringly, as shown in the output table, conditioning the parallel trends on these covariates leads to point estimates statistically equivalent to the original specification.



Note: The graphic is based on Table 3 with the calorie intake threshold at 2,100 kcal. Blue dots are the point of estimate in each normalized treatment period and the red lines are the confidence interval.

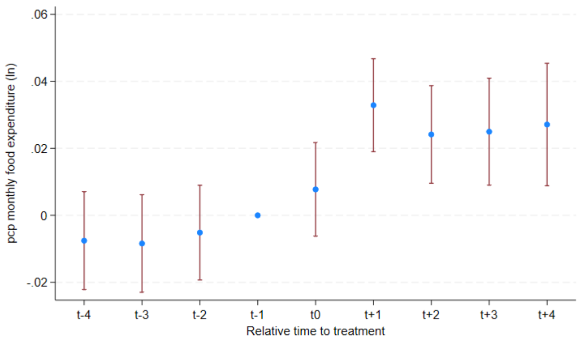
Figure 3. Event study plot - food security

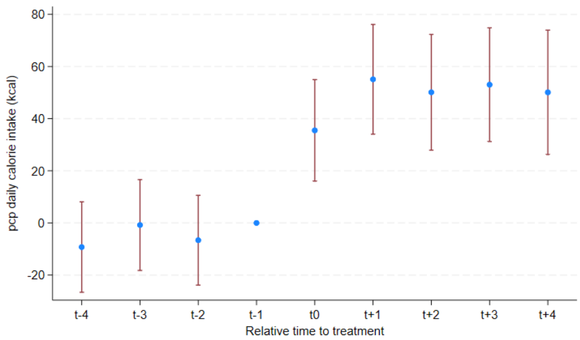
4.1.2. The effect on food consumption and calorie intake

We further explore the effect of OFD on the elements that construct our food security indicator, which is food consumption. Specifically, we run the regression with two outcome variables: food expenditure and calorie intake. The graphical representation of the event study is shown in Figure 4 and the estimation results are presented in the first two columns of Table B.1.

From the output table, we can observe that OFD penetration leads to an increase in per capita food expenditure with an overall effect of 2.4 pp, which achieves 1% statistical significance. The increase begins a year after the penetration (t+1) and remains similar in the subsequent periods. The low magnitude of effect in the year of penetration suggests an adaptation process. While consumers learn the new way of ordering food; food enterprises learn to enter the OFD market. However, such an in spending on food does not necessarily mean households consume more food. One can spend more on food while consuming the same amount due to an increase in food prices. To confirm whether OFD affects food consumption in terms of quantity, we use calorie intake as the outcome variable. As shown in Column 2, overall, OFD increases the aggregated household daily calorie intake by 54.7 kcal. The treatment effect started from period 0 at an increase of 36.4 kcal and consistently showed a higher-level effect in the next periods. This confirms that households eat more food due to the entry of OFD in their respective districts. The individual and joint pre-trends in both estimations are statistically insignificant, providing support for parallel trend assumption.

Delving further, we present the impact of OFD on decomposed nutritional intakes. This will explain through which nutritional channel the food security is affected by the penetration of OFD service. As shown in Table 3, we run the regression separately for carbohydrate, protein, and fat, all measured in grams. We use the same estimator and the same specification as the main regression. We found evidence that, overall, OFD increases households' daily intake of carbohydrate, protein, and fat by 7.74 gr, 1.97 gr, and 2.26 gr, respectively. In terms of calories, these are equivalent to 29.96 kcal, 7.88 kcal, and 20.34 kcal. Similarly to the pattern in the previous estimates, the treatment effect is relatively low at lag 0, but rises in the next period and remains relatively constant afterward. In this estimation, we can only claim the parallel trend assumption on the estimation of carbohydrates. The individual and joint pre-trends of carbohydrate estimate are insignificant. For the protein estimate, the join pre-trend test is statistically insignificant but there is a significant pre-trend on lead 2, rejecting the hypothesis that no difference in pre-trends between the treatment and control group. For the fat estimate, the joint pre-trends test is significant at 1% level.





Note: The graph is based on Table B.1. The outcome of the left figure is food expenditure (ln) and the outcome of the right figure is calorie intake (kcal). Blue dots are the point of estimate in each normalized treatment period and the red lines are the confidence interval.

Figure 4. Event study plot - food expenditure and calorie intake

Thus, by far, we only have strong evidence of causality in the relationship between OFD platform penetration and carbohydrate intake. Although we observe the increase in each type of nutritional intake, we cannot properly assess whether such an increase is good or bad health implications because we do not have data on nutritional threshold needs, which may vary across individuals depending on their characteristics. We also do not have data on health performance such as obesity and food-related diseases. Future studies may consider investigating it.

4.2. Falsification and Robustness Test

We interrogate our main estimation result in several ways. First, we provide estimation results using alternative treatment assignments, which are based on online scrapping and ML prediction. Second, we use different outcomes constructed from questions about food insecurity experience. Third, we employ other modern event study estimators. Fourth, we revisit our parallel trend assumption with a couple more rigorous tests. Last, to check the anticipation effect, we falsify our treatment by shifting the treatment timing by one period.

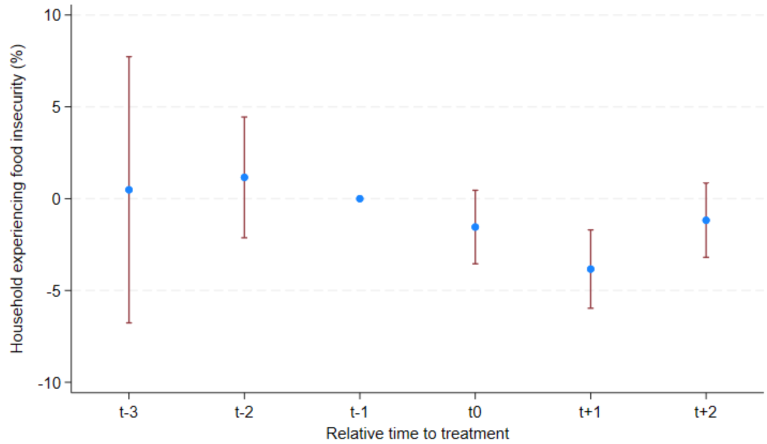
4.2.1. Alternative Treatment Assignment

In our preferred estimation, we define treatment by using a combination of online scrapping and machine learning, as explained in Subsection 3.1. We now provide separate estimation results purely based on the two treatment assignments. As shown in Table C.1, the results are consistent with the main finding that OFD penetration increases food security, regardless of the inclusion of the covariates. The effect estimate of the online scrapping method is lower at 3.4 pp compared to the ML method at 3.8 pp.

4.2.2. Alternative Outcome

We provide estimation using different outcomes based on subjective food insecurity experience. Susenas has a section about food insecurity experience that consists of 8 questions. Households are asked whether they have ever experienced not having enough food, a decrease in the quality of nutritious food, a decrease in diversity of food, a decrease in the frequency of eating, a reduction in food portion, running out of food being hungry but unable to eat and not eating at all within a day. These data are commonly used in studies on food insecurity in Indonesia Ardianti et al. (2023). We construct two variables of food insecurity experience: (1) the district's average score of the sum of households' food insecurity experience score (ranging from 0 to 8) and (2) the percentage of households in the district who ever experienced at least one of the 8 food insecurity questions. The higher the percentage the more people are suffering from food insecurity.

We perform regression on the new indicators with the same SA estimator. However, since questions on food insecurity experience are only available starting from Susenas 2017, we trim the periods before 2017. Given shorter periods, our specification incorporates two leads and three lags, including the treatment at period 0. Similar to the main regression, the baseline period is one year before treatment and the control cohort is the never-treated group. Furthermore, we constructed the treatment group as a sample of districts that were penetrated by OFD from 2018 onward. This way, all districts in the selected sample were non-treated in 2017.



Note: The graphic is based on Appendix D column 4. The outcome is the percentage of households experiencing subjective food insecurity. Covariates are included. Blue dots are the point of estimate in each normalized treatment period and the red lines are the confidence interval.

Figure 5. Event study plot - food insecurity experience

The estimation results, presented in Table C.2, confirm our main finding, despite using alternative outcome indicators. As shown in Figure 5, the penetration of OFD platforms reduces the food insecurity experience by an overall effect of 2 pp. The magnitude of the effect is relatively low at the year of penetration with a decrease in food insecurity experience by 1.5 pp and then a higher magnitude in the next period. The pretend is statistically insignificant, providing support for the parallel trend assumption.

4.2.3. Alternative Event Study Estimators

In this subsection, we look at the robustness of our estimates to other staggered DiD designs. We provide several estimators, including De Chaisemartin and d'Haultfoeuille (2024), Callaway and Sant'Anna (2021), and Wooldridge (2021). Similar to the SA estimator, the alternative estimators generate valid treatment-control group comparisons to avoid the negative weights issue which causes TWFE estimates biased when treatment effects are heterogeneous across periods and groups. They differ from SA in the regression framework, choice of control, base period setup, and accommodation of unbalanced panel data. The regression results are presented in Table C.3. Consistently, all specifications show a positive and significant effect of OFD on food security, ranging from 2.1 pp to 4.6 pp. However, none of these estimations achieve parallel trend assumption as the joint pre-trends test is statistically significant.

4.2.4. Parallel Trend Test

While we have shown the evidence supporting parallel trend assumption in our main estimation, recent studies show concern about the validity of testing pre-trends due to the low statistical power (Roth, 2022). We run a more rigorous test, developed by Roth (2022), which investigates limitations of conventional pre-trends analysis and demonstrates powerenhaced pre-trend test to detect potential violation of parallel trends. Figure C.1shows the output of the test with an assumption of 80% statistical power. The test shows the impact of the potential misdiagnosis of insignificant pre-trends and pretesting on those pre-trends. The result suggests that the "true effects" - shown by the red line - and mean effects - shown by the blue dashed line - inside the confidence intervals for the estimated treatment effects in only lag 4. It suggests that our estimation has strong support for the parallel trend assumption only in lag 4.

In addition, we utilize a procedure proposed by Rambachan and Roth (2023) to examine the sensitivity of treatment effects estimation to violations of parallel trends assumption. This test considers differential shocks to treatment and control groups that generate violations to parallel trends assumption. An estimation is robust as long as post-treatment violations are less than 1 times the maximum pre-treatment violation. Figure C.2 shows the output of Rambachan and Roth (2023). For the test on lag 4, all lines do not include zero before the value of the x-axis turns to 1, indicating that the result is not sensitive to the violation of the parallel trend assumption. However, this is not the case for the test on lag 3, casting doubt on its parallel trend.

4.2.5. Anticipation Test

Another underlying assumption in the SA estimator is no anticipation effect, referring to the condition that treatment has no causal effect prior to its implementation. To test this, we shift the treatment timing by one period forward and rerun our main regression. As shown in Figure C.3, we do not find a statistical significance at the point estimate for the treatment effect in the period just prior to the OFD entry (i.e. at Lag 0 in the revised specification), suggesting no anticipation effect.

4.3. Extended Analysis

To this end, we have confirmed the effect of OFD on food security. This section will elaborate further on the possible mechanisms underlying our main findings. We also conduct heterogeneity analysis aimed at better understanding different impacts across groups with different characteristics.

4.3.1. Possible Mechanisms

We suspect several underlying mechanisms for how OFD increases consumption and thus food security. On the demand side of food market, the introduction of OFP platforms can possibly change at least two things: consumer preference and consumer income. Regarding consumer preference, the convenience of OFD services makes it easier for people to access a variety of foods without the need to travel or cook, which can lead to more frequent ordering. Consumers have access to a wide range of restaurants and cuisines that they might not have otherwise. This variety can lead to increased experimentation with different foods. The user interfaces of OFD apps are designed to promote impulse buying through recommendations and highlighted deals, which can lead to increased food consumption. Furthermore, OFD platforms often offer promotions, discounts, and incentives that can encourage higher spending and more frequent orders. These promotions might also steer consumers toward higher-calorie options that are more profitable for the platforms or restaurants. Nevertheless, given the data unavailability, testing the mechanism of the effect of OFD platforms through consumer preference is beyond the scope of this study.

As for channel through income, with the penetration of OFD platforms, household members can join as partners (drivers or merchant sellers) and thus gain more income. In another way, household members who were in charge of cooking now have the option to order food online and use their time in more productive way, leading to higher income. As the income data is not available in the Susenas, we use two proxies, which are sector-based GDRP (non-oil) and unemployment level. The regression results are reported in Table 4. We observe a null effect on GDRP and a negative impact on the unemployment level. However, the estimation on unemployment cannot satisfy the parallel trend assumption as the joint pre-trends test shows a significant result, casting doubt on the causal relationship. Therefore, we do not have strong evidence to support the income hypothesis.

Table 4. The effect of OFD on selected outcomes

	Non-oil GRDP	Unemployment rate	Unit price	Workers in food sector
Lead 4	0.006	-0.074	-0.005	
	(0.004)	(0.203)	(0.006)	
Lead 3	0.014	0.297	-0.007	
	(0.014)	(0.213)	(0.006)	
Lead 2	0.003	0.543***	-0.001	-168.809
	(0.003)	(0.199)	(0.006)	(626.269)
Lag 0	0.004	-0.020	-0.005	378.214
	(0.003)	(0.190)	(0.005)	(612.276)
Lag 1	0.005	0.282	0.014**	1671.856***
	(0.004)	(0.225)	(0.006)	(541.886)
Lag 2	0.004	-0.891***	0.007	2025.121***
	(0.005)	(0.229)	(0.006)	(510.881)
Lag 3	-0.006	-0.677***	0.007	
	(0.006)	(0.208)	(0.006)	
Lag 4	-0.007	-0.781***	0.008	
	(0.006)	(0.230)	(0.007)	
Overall ATT	0.002	-0.417***	0.006	1358.39***
	(0.004)	(0.148)	(0.005)	(334.06)
Joint pre-trends test				
Prob > chi2	0.3372	0.015	0.6480	0.7875
Covariates	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N districts	514	514	514	363
N observations	5630	5645	5653	2178

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

On the supply side, the penetration of OFD may induce people to start or expand businesses in the food market. The increase in competition in the food market may lead to lower price, higher quality, or more variants of foods. We first test whether there are more people working in the food sector. As shown in Column 4, we confirm this hypothesis. Delving further on the impact on the unit price, calculated by dividing food expenditure by calorie intake, we do not have evidence of causal impact. While a positive impact is observed in t+1, we found overall null effect.

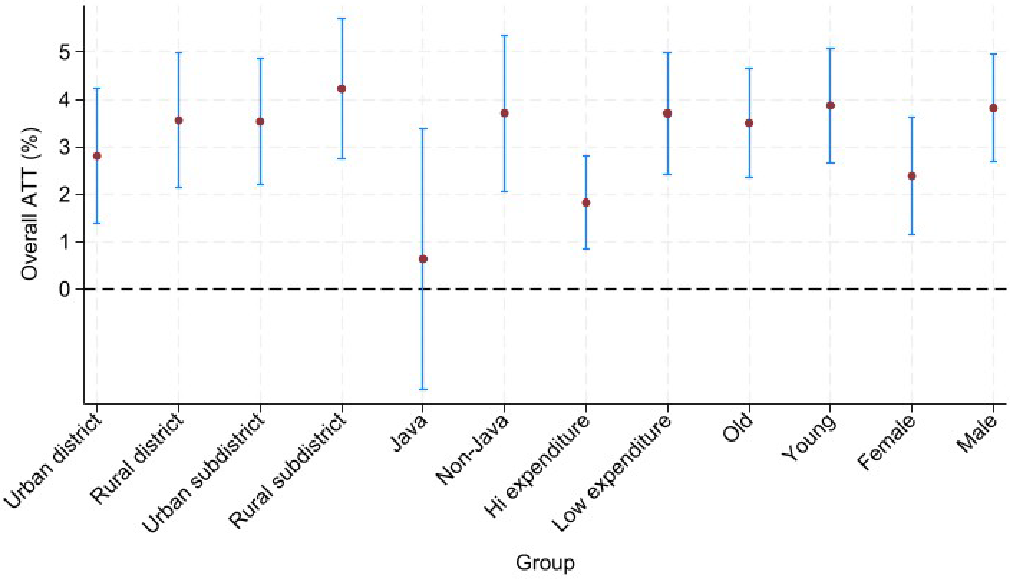
4.3.2. Heterogeneity Analysis

We provide heterogeneity analysis based on geographical location and household characteristics. The full regression results are reported in Table B.2.1 and Table B.3.1and the overall treatment effects are presented in Figure 6.
For the location-based heterogeneity, we split our observation of districts into urban group and rural group based on administrative classification 5. We see that the effects of OFD proliferation on food security are notably higher in rural areas compared to urban areas, with an overall effect of 3.6 pp as opposed to 2.8 pp. The same pattern with a larger difference is observed when comparing Java (more urbanized Island) and non-Java districts with an effect of 0.6 pp as opposed to 3.7 pp. However, we cannot rule out the possibility that the predominance of lower effects for urban districts may be a function of the limited sample size and statistical power concerns due to sample split. To overcome this issue, we compare rural subdistricts and urban subdistricts6. Note that our observation is still at the district level, but we construct the aggregated outcome variable based on the subdistrict's location. Even with this change, the finding remains consistent. Food security increase is higher among rural subdistricts than urban subdistricts.

We argue that the introduction of OFD in rural districts may represent a more significant change in lifestyle and convenience compared to urban districts where such services are often already established and part of daily life. The novelty factor and the cultural shift towards modern convenience in rural districts might lead to a more noticeable immediate impact as communities transition from traditional food procurement and consumption patterns to more modern ones facilitated by technology. Moreover, in urban districts, consumers often have easier access to a wide variety of food outlets and quicker delivery options due to higher population density. In contrast, rural districts may have limited food outlets, and online food delivery services can significantly increase the variety of food options available to consumers who otherwise would have to travel long distances to access similar variety.

For the household characteristics-based heterogeneity, we do not split the observation. Instead, we reconstruct the outcome variable based on household characteristics. For instance, we calculate the aggregate food security among households headed by male and use it as an outcome. We then conduct a separate regression using a different outcome based on female-led households. This way, the number of observations remains the same as our main estimation.

The result suggests that a higher impact of OFD on food security among households with lower expenditure (bottom 40% of expenditure distribution) compared to that of higher expenditure (Upper 60% of expenditure distribution) with 1.8 pp. People at the bottom of expenditure (or arguably income) distribution benefits more from he OFD penetration as they gain better access, consistent with our finding regarding rural-urban comparison. Furthermore, younger households (under 40 years old household head) has higher impact at 3.8 pp as opposed to older households (above 40 years old household head). This is sensible as the younger population are more aware of technological change. Another difference is observed across gender with male-lead household gain higher impact at 3.8 pp compared to female counterparts at 2.4 pp.



Note: The graph is based on the estimation result in Table B.2 and Table B.3. Blue dots are the point of estimate in each normalized treatment period and the red lines are the confidence interval. The outcome is the food security rate based on the 2,100 kcal threshold.

Figure 6. The effect of OFD platforms across groups

4.3.3. Household Analysis

Thus far, we have analyzed the impact of online food delivery platforms on food security at the district level. In this section, we dive further into household-level analysis using data that allow us to identify whether a household ever uses an online food delivery platform. In addition, we run the analysis in the context of COVID-19, when food security became a major global concern (Mardones et al., 2020; Saboori et al., 2022; Zhu et al., 2022), especially among low-income people (Fang et al., 2022).

We utilize publicly available data from a high-frequency phone-monitoring survey of households conducted by Worldbank (Ali et al., 2023). The survey aimed to provide rapid insights on the socio-economic impact of COVID-19, consisting of 8 rounds spanning from May 2020 to April 2023. We specifically utilize rounds 3 and 4 which contain our variable of interests which was conducted in July 2020 and November 2020, respectively. In all survey rounds, including round 4, people were asked 5 questions about past food insecurity experiences, for instance, ”During the past week, was there a time when your household had food shortage because of lack of money or other resources?”. We assign 1 if the respondent answered ”yes” and 0 otherwise. We then construct the main outcome as a dummy, whether households have ever gone through at least one of five food insecurity experiences. To check the intensive margin, we also construct another alternative outcome, which is the sum of the values for five questions, meaning that 5 is the worst condition and 0 is the best condition.

Our treatment variable is a dummy of whether households have ever used OFD services since March 2020. This information is obtained in survey round 4. Households were asked whether they started or increased using online platforms to purchase their food needs and what type of payments were used. We utilize a set of covariates including income, and the number of household members. We also include characteristics of household heads like sex, age, and education. We run non-linear regressions with the following specification:

$$\ln\left(\frac{y_i}{1-y_i}\right) = \propto_0 + \propto_1 OFD_i + \beta X_i \tag{3}$$

We present the output in Table 5. Columns 1 and 2 are logistic regressions with dummy food insecurity as the dependent variable. The result shows that the utilization of OFD is associated with lower food insecurity, after controlling for income and other covariates. Households who use OFD services are associated with a 12% lower likelihood of being food insecure. Columns 3 and 4 are Poisson regressions with food insecurity score as the dependent variable. Similarly, we found that households with access to OFD services are associated with lower food insecurity scores.

Table 5. OFD utilization and food insecurity during COVID-19 pandemic

	Dummy food insecurity		Food insecurity score	
	Point estimate	Marginal effect	Point estimate	Marginal effect
OFD utilization (=1)	-0.526***	-0.120***	-0.418***	-0.373***
	(-5.12)	(-5.20)	(-5.06)	(-5.03)
Income (ln)	-0.383***	-0.0873***	-0.231***	-0.206***
	(-9.98)	(-10.62)	(-10.90)	(-10.64)
Covariates	Yes	Yes	Yes	Yes
N	3178	3178	3178	3178
Pseudo R2	0.0479		0.0419	

Note: Robust standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Our finding is in line with Wang et al. (2022) which shows how OFD platforms contribute to the resilience of the food system in China in response to the unexpected external shock of COVID-19. Their study revealed that certain restaurants remained operational and provided OFD services during lockdowns, experiencing additional growth after the lockdowns were lifted. Similarly, in Indonesia, many areas implemented full or partial lockdowns, restricting people from purchasing food in person. However, OFD services helped overcome these accessibility constraints, enabling people to obtain food.
However, our household-level analysis does not provide causal evidence. We cannot claim that the assumption of unconfoundedness is fully satisfied. Our treatment variable, OFD utilization, is not randomly assigned. While we have included several covariates and reverse causality appears unlikely in this context, we cannot rule out the possibility of endogeneity issues, such as omitted variable bias.

5. Conclusion

This paper examines the impact of the emergence of OFD services on district-level food security in Indonesia. By utilizing data from the consumption section of Susenas, spanning 2012 to 2022, and integrating it with newly gathered information on OFD service introductions across districts—obtained through internet scraping and machine learning—we employ a contemporary event-study approach to analyze the data. Our results reveal that the expansion of OFD services leads to a significant improvement in food security. Specifically, it increases the level of food security by approximately 2.7 percentage points. Additionally, we observe a rise in food expenditure and calorie intake, driven primarily by an increase in carbohydrate consumption. These findings are robust across various model specifications and withstand a falsification test. They also satisfy the parallel trend assumption and show no anticipation effects—key requirements of the event-study methodology—reinforcing the credibility of our causal inferences. Furthermore, our household-level analysis indicates a consistent relationship between access to OFD services and food security compared to our district-level analysis.

Our heterogeneity analysis indicates that the positive effects are stronger in rural areas, districts outside Java, households with younger heads and male heads, and among households with lower expenditures. Regarding mechanisms, we find no evidence of an income effect that enhances the ability to purchase food. Instead, we suggest that the observed outcomes may be driven by increased competition in the food market.

Nevertheless, additional case studies from other countries are needed to assess whether our results are valid beyond Indonesia. We also do not examine the implications of varying levels of OFD usage within treated districts on the differences in food insecurity across districts. Moreover, we do not investigate the broader impacts of OFD services on related issues such as health outcomes and labor market dynamics. We argue that these aspects fall beyond the scope of this paper. Future research could explore these broader implications associated with OFD services.

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Author Contributions (CRediT)

Pyan A. Muchtar: Conceptualization, data curation, formal analysis, funding acquisition, methodology, software, validation, visualization, writing – original draft. Budy P. Resosudarmo: Conceptualization, formal analysis, methodology, supervision, validation, writing – review and editing.

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Declaration of generative AI and AI-assisted technologies

During the preparation of this work the authors used Grammarly to proofread the language and ChatGPT to check Stata error code. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A Data Structure

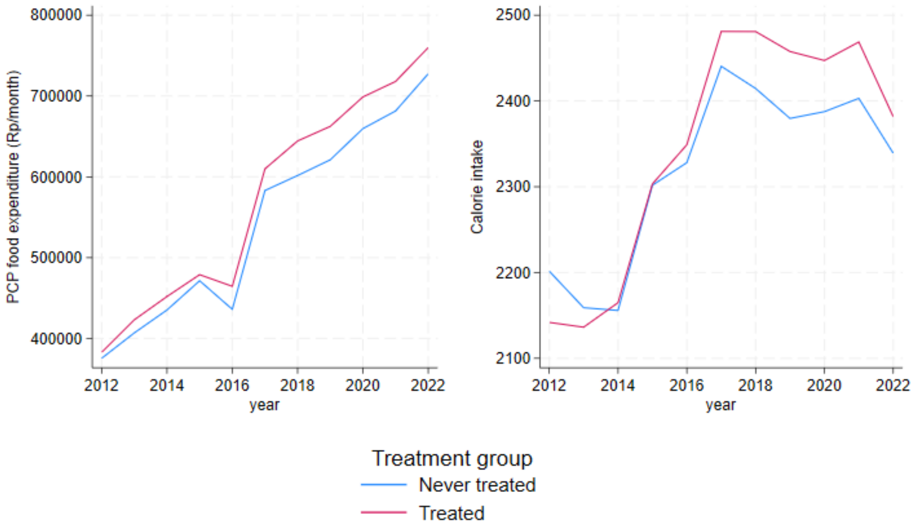


Figure A.1. Mean trend of food expenditure and calorie intake

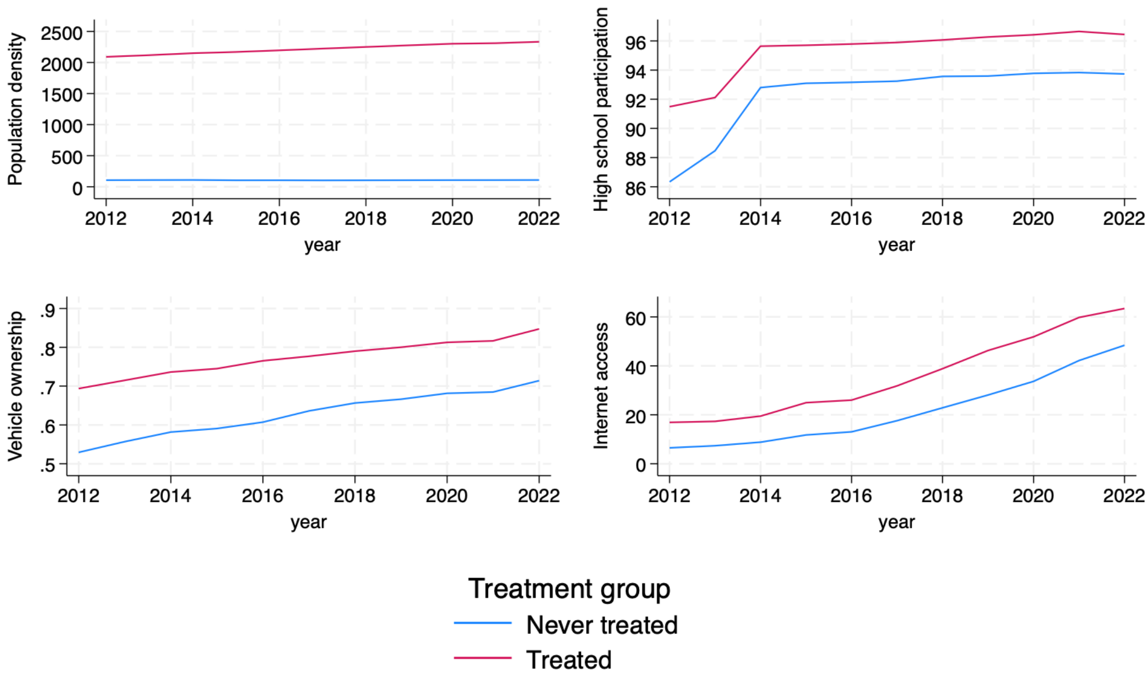


Figure A.2. Mean trend of selected covariates

Table A.1. ML prediction results across methods

Class function	Best Hyperparameter	Held-out set (Java-Sumatra)		Prediction 1 (Non JS)		Prediction 2 (Non-JS treated)	
		Accuracy	f1-score	Accuracy	f1-score	Accuracy	f1-score
Penalised logistic regression	C-value: 2.78 l1: none	92%	87%	81%	53%	80%	79%
K-nearest neighbor	n neighbors: 3 metric: minkowski	94%	91%	76%	47%	80%	79%
Support vector machine	kernel: rbf gamma: auto	93%	94%	86%	52%	79%	72%
Random forest	n_estimators: 65 max_feature: 5 bootstrap: false	97%	95%	93%	73%	85%	82%
N training (district-year)		2340		2926		2926	
N test (district-year)		586		2687		770	

Note: The unit level of the data is at district-year. The label (outcome) is a dummy whether the district in the particular year has been penetrated by OFD. All models use the same features (covariates), including geographical variables, socioeconomic indicators, and demographic indicators. The ML classifier selects optimal features based on its algorithm. Hyperparameters are selected based on k-fold cross-validation with accuracy and f1-score as the objective. Accuracy is a metric that measures the percentage of all correctly identified cases. f1 score is the harmonic mean of Precision and Recall. Precision measures the proportion of true positive predictions among all positive predictions while Recall measures the proportion of true positive predictions among all actual positive instances.

Appendix B Additional Results

Table B.1. The effect of OFD on food expenditure and calorie intake

	Food consumption		Nutritional intake		
	Expenditure (ln)	Calorie (kcal)	Carbohydrate (gr)	Protein (gr)	Fat (gr)
Overall ATT	0.024***	54.688***	7.744***	1.970***	2.262***
	(0.006)	(9.093)	(1.349)	(0.306)	(0.318)
		Joint pre-trends test			
Prob > chi2	0.669	0.744	0.661	0.251	0.009
Covariates	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N districts	514	514	514	514	514
N observations	5,630	5,630	5,630	5,630	5,630

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Table B.2. Location-based heterogeneity

	District category		Subdistrict category		Location	
	Kota (urban)	Kabupaten (rural)	Kelurahan (urban)	Desa (rural)	Java	Non Java
Overall ATT	2.804***	3.558***	3.535***	4.223***	0.632	3.708***
	(1.147)	(0.726	(0.677)	(0.757)	(1.408)	(0.841)
Joint pre-trends test						
Prob > chi2	0.748	0.438	0.891	0.662	0.534	0.375
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N districts	514	514	514	514	514	514
N observations	1,078	4,575	5,341	5,198	1,304	4,326

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Table B.3. Households characteristics-based heterogeneity

	Expenditure class		HH head age group		HH head sex	
	U60	B40	Older	Younger	Female	Male
Overall ATT	1.820***	3.702***	3.502***	3.872***	2.384***	3.814***
	(0.502)	(0.651)	(0.580)	(0.619)	(0.627)	(0.583)
Joint pre-trends test						
Prob > chi2	0.737	0.429	0.869	0.472	0.232	0.759
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N districts	514	514	514	514	514	514
N observations	5,630	5,630	5,630	5,630	5,630	5,630

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Appendix C Robustness Checks

Table C.1. Estimation results with alternative treatment assignments

	Dep var: food security			
	Online scraping		ML prediction	
	No cov	With cov	No cov	With cov
OFD penetration	3.410***	3.427***	3.816***	3.823***
	(0.568)	(0.574)	(0.568)	(0.574)
Joint pre-trends test				
Prob > chi2	0.562	0.655	0.606	0.632
Covariates	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N districts	514	514	514	514
N observations	5653	5630	5653	5630

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Table C.2. The effect of OFD on food insecurity

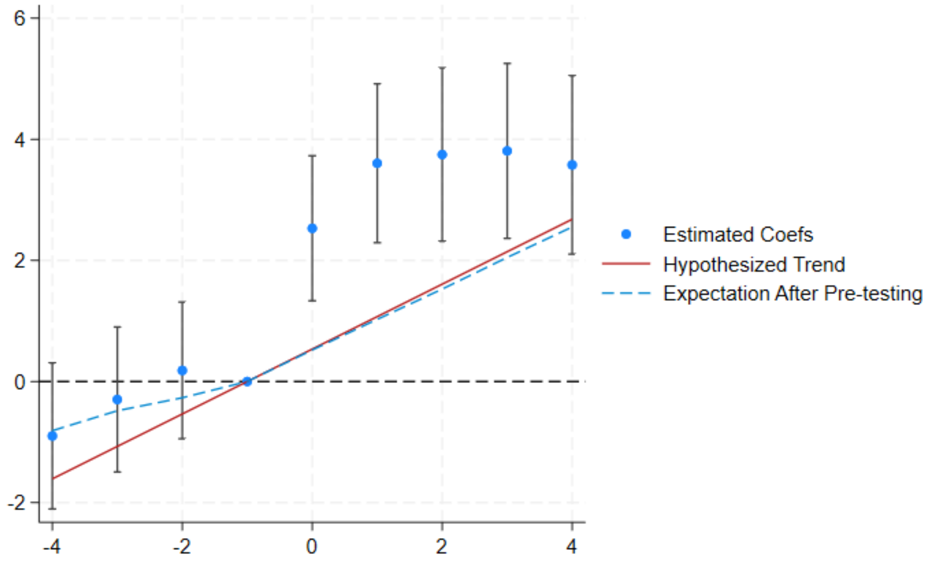
	Average insecurity score		Percentage of insecure HH	
	No cov	With cov	No cov	With cov
T – 3	0.050	0.044	3.239*	3.111
	(0.041)	(0.043)	(1.918)	(1.948)
T – 2	0.034	0.029	1.810	1.690
	(0.040)	(0.040)	(1.202)	(1.199)
T = 0	-0.027	-0.024	-1.647*	-1.569*
	(0.026)	(0.026)	(0.942)	(0.950)
T + 1	-0.092***	-0.092***	-3.818***	-3.823***
	(0.026)	(0.027)	(1.016)	(1.019)
T + 2	-0.008	-0.010	-0.657	-0.752
	(0.029)	(0.028)	(1.066)	(1.047)
Overall ATT	-0.041**	-0.042**	-2.041***	-2.047***
	(0.019)	(0.019)	(0.734)	(0.731)
Joint pre-trends test				
Prob > chi2	0.406	0.513	0.0937	0.124
Covariates	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N districts	344	344	344	344
N observations	2064	2064	2064	2064

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels

Table C.3. Estimation results best on different alternative estimators

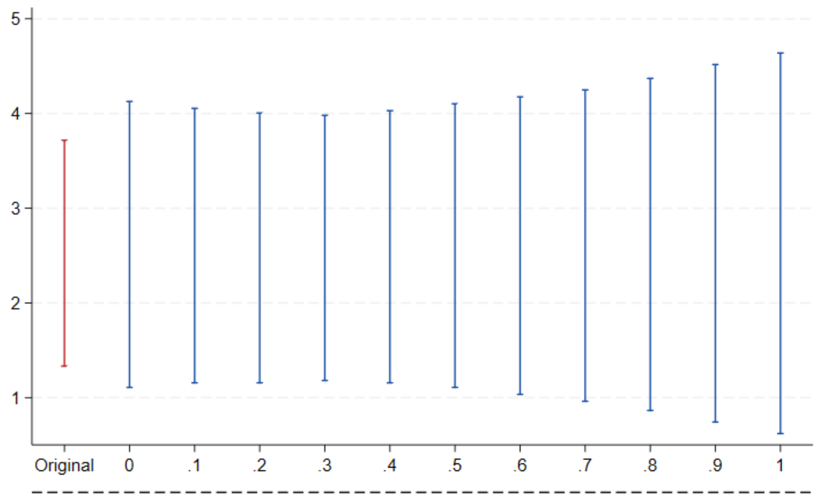
	Woolridge (2021)		de Chaisemartin and D'Haultfuille (2022)		Callaway and Sant'Anna (2021)	
	(a)	(b)	(a)	(b)	(a)	(b)
Overall ATT	4.566***	2.344***	2.156***	2.466***	2.149***	2.344***
	(0.726)	(0.712)	(0.654)	(0.684)	(0.698)	(0.706)
Control group	Not yet	Never	Not yet	Not yet	Not yet	Never
Covariates	No	No	No	Yes	No	No
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N districts	514	514	514	514	514	514
N observations	5653	5653	5653	5630	5653	5653

Note: District-clustered standard errors are in parentheses. *, **, *** denote statistical significance at 0.1, 0.05, and 0.01 levels



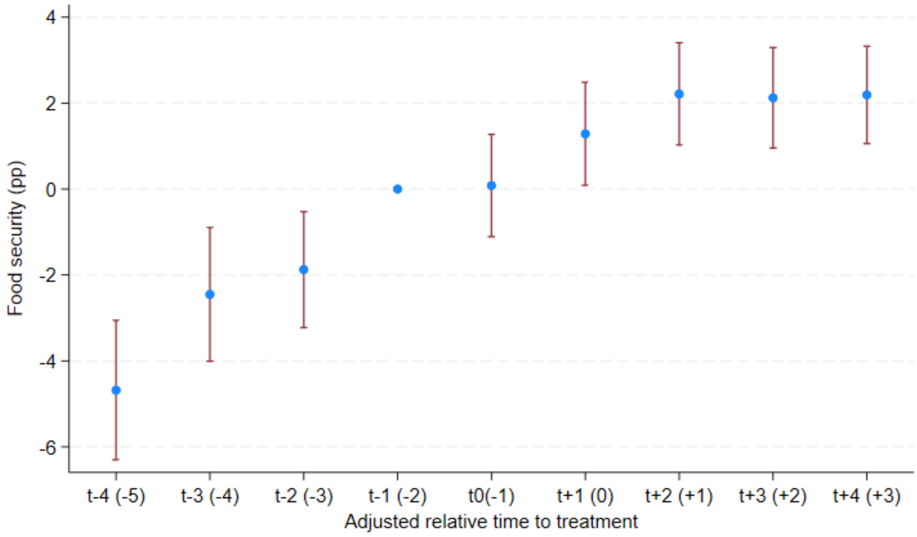
Note: The test is conducted on the regression from Table 2 with calorie threshold at 2,100 kcal. It displays the results of the hypothesized violations of parallel trends, calculated using 80% probabilities of rejecting the pretest. The slopes of the linear violations are 0.514. The solid red line shows the hypothesized linear trend based on the slope, while the dashed blue line shows the coefficients under the assumption that no significant pre-trend exists, conditioned on the red line being the true trend. The dashed blue lines are used to identify potential issues with pretesting.

Figure C.1. Roth (2022) test result



Note: The test is conducted on the regression from Table 2 with calorie threshold at 2,100 kcal. The test adjusts the model to account for non-parallel pre-treatment trends and examines the sensitivity of the treatment effect estimates to variations from these trends prior to treatment. The x-axis represents the relative size of the violation allowed during the post-treatment period. The y-axis is the treatment effect. The vertical lines indicate the confidence interval across states of parallel trend violation.

Figure C.2. Rambachan and Roth (2023) test result



Note: The outcome is districts' food insecurity with the calorie intake threshold at 2,100 kcal. Blue dots are the point of estimate in each normalized treatment period and the red lines are the confidence interval. Treatment time is shifted one period forward. Numbers in parenthesis are the actual periods.