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Impact of Super Apps on the Nutrition Transition in Low- and Middle-Income Countries: Evidence from Indonesia

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Abstract

Many low- and middle-income countries (LMICs) are experiencing a nutrition transition from traditional diets to high-energy, processed foods, increasing non-communicable disease risks. Digitalization of food systems plays a significant role in shaping this transition. This paper investigates the impact of super app expansions (including food delivery, ridesharing, and other daily life assistance) on nutritional outcomes and the underlying mechanisms. Staggered district-level adoption of Indonesia's two largest digital platforms, Gojek and Grab from 2015 to 2018, is used. This information is combined with the health dataset from Indonesia's Basic Health Survey (Riskesdas) and food consumption data from the National Socioeconomic Survey (Susenas). To address the endogeneity issue associated with the correlation between super app entry decisions and nutritional outcomes, we use doubly robust difference-in-differences, which incorporates baseline covariates ensuring a conditional parallel trend. The results show that super apps contribute to an increase in BMI scores, particularly among individuals who are already overweight and obese. This effect is especially driven by the online food delivery feature and is more pronounced in cities than regencies and among individuals with employment, above median income, and education beyond primary school. These increases could be attributed to unhealthy food consumption (i.e., salty and prepared foods). Our findings suggest that super apps may exacerbate malnutrition. On the other hand, we find underweight reduction in the cities and an overall increase in fruit and meat consumption, indicating super apps' potential to improve malnutrition. These findings highlight the role of super apps in the nutrition transition in LMICs.

Keywords: digital platform, super app, online food delivery, nutrition transition, overweight, obesity

JEL Codes: I15, O14, R40

1 Introduction

The nutrition transition, marked by the shift from traditional staple diets to high-energy-density diets and processed foods, is a rising concern in many LMICs (Brouwer et al., 2021). This is exacerbated by the digital transformation of the food system that discourages active lifestyles and promotes unhealthy diets, leading to an increase in non-communicable diseases such as obesity, diabetes, and high blood pressure (Bennett et al., 2024; Popkin, 2017). Digital platforms, modern marketing, and access to out-of-home food (Granheim et al., 2021; Andreyeva et al., 2011) represent the novel aspects of the food systems transformation that remain underexplored. Currently, many on-demand companies create super apps that offer a wide range of services (i.e., food delivery, ride hailing, e-commerce) within a single platform as a one-stop solution to enhance convenience and accessibility. While such services might improve an individual's convenience and access to resources, they might negatively affect one's health by encouraging unhealthy lifestyles and food consumption. Previous studies have indicated how super apps presence is associated with less physical activity and increased promotion of highly processed and calorie-dense meals (Maimaiti et al., 2018; Horta et al., 2022). With more than a third of the adult population affected by obesity (World Health Organization, 2016), understanding the impact of these services becomes ever more important. This study aims to address this gap by investigating the effect of super apps on nutritional outcomes and food consumption using digital platform expansion in Indonesia.

While earlier studies have mostly examined user characteristics of food-related digital platforms, the broader impact of these platforms and their impact pathways on the nutrition transition remains underexplored. Previous studies highlighted that users tend to be young people and those more affluent and have a sedentary lifestyle due to their work (Safira and Chikaraishi, 2022; Dana et al., 2021; Dominici et al., 2021; Keeble et al., 2021). However, most of these studies explore association and it remains unclear whether exposure to such services negatively affects healthier individuals. As most food offered on such platforms typically has lower nutritional quality, understanding if improved access to delivery food leads to increased unhealthy food consumption and consequently affects nutritional status, remains an important empirical question to answer (Meemken et al., 2022). To explore how exposure to super apps affects nutritional outcomes, we take advantage of the staggered adoption of digital platforms in Indonesia. By comparing nutritional status and food consumption before and after the introduction of super apps among those exposed and not exposed, we provide unique insights into the intersection of digitalization and the nutrition transition in the LMICs context.

This study draws on the food environment construct developed by Turner et al. (2018), the point of connection where people interact with the wider food system to obtain and consume food. Using the personal domain of the food environment, we argue that the digitalization of food systems through super apps affects the accessibility, affordability, convenience, and desirability of different food sources. These changes enable the consumption of more processed and energy-dense foods, contributing to rising overweight and obesity rates in LMICs. Digital food services often influence food outlets' expansion, especially in "food deserts", where there is a shortage of healthy food supply (Bennett et al., 2024; Keeble et al., 2022; Brandt et al., 2019). Additionally, the excess processed and junk food groups advertised through the app such as pizza, sandwiches, sugar-sweetened beverages, ice cream, and salty packaged snacks, may further exacerbate unhealthy food consumption (Horta et al., 2022; Andreyeva et al., 2011). For those who have limited time to prepare food and can afford to purchase delivery food, buying commercially prepared food ensures convenience and accessibility (Safira and Chikaraishi, 2022; Dana et al., 2021; Dominici et al., 2021; Maimaiti et al., 2018).

On the other hand, previous studies also indicate that digital technology has a role in improving food security and the nutrition transition. Technology can help alleviate difficulties in accessing healthy food by improving access and information to more diverse diets (Brandt et al., 2019; Bennett et al., 2024; Pearson et al., 2014). These platforms often implement strategies to ensure consumer loyalty through discounts and price reduction strategies (Tong et al., 2020; Nguyen et al., 2019), enabling the poorer groups to access more diverse food products. Previous studies also indicate increased income among drivers and merchants – also known as gig workers (Berger et al., 2018, 2019) which can also play a role in ensuring households' dietary diversity. As income data in LMICs tends to be underestimated, this study will explore income-related demand changes using expenditure data as a proxy.

In many LMICs, there has been a massive expansion of on-demand digital platforms assisting daily life activities, challenging traditional business processes where transactions usually require a reasonable amount of physical interactions and activity (Li et al., 2020). In Southeast Asia, this phenomenon is represented by the expansion of the two largest on-demand companies, Gojek and Grab. Both companies initially built their market in Indonesia in 2015 and have since developed super apps that offer food delivery and other services such as ridesharing, logistics delivery, financial support, and domestic care assistance (Safira and Chikaraishi, 2022; Azzuhri et al., 2018). They have revolutionized the food industry by enabling smaller restaurants to open a joint operation and individual kitchens to operate without traditional physical locations, using home kitchens, pick-up lockers, and curbside parking lots (Ahuja et al., 2021; Meemken et al., 2022). Loyal consumers can spend over 20% of their monthly income on such platforms, often incentivized by extra discounts and promotional offers (Tong et al., 2020; Horta et al., 2022), highlighting their significant influence on consumption behavior.

We use the district expansion of super apps from Gojek and Grab in Indonesia from 2015 to 2019, to investigate the effect of food-related digital platforms on nutritional outcomes using a difference-in-differences approach. This approach compares nutritional outcomes and food consumption aggregated at the district level, measured by BMI, waist circumference, nutritional status (i.e., overweight, obesity, underweight), and different food group expenditures, of districts exposed and not exposed to the platforms. Additionally, we conduct a heterogeneous treatment effects analysis to assess super apps' impact across districts with different socioeconomic statuses. This study also explores individual level analyses using quantile regression and heterogeneous effect analysis to assess super apps' effect across BMI distribution and identify vulnerable groups in the population based on demographic characteristics.

Our findings show that districts with super apps have higher BMI scores and overweight/obesity incidence than districts without super apps. The impact of these platforms is driven by the food delivery feature and is more pronounced in cities and districts with higher economic output. Individuals with BMI scores categorized as overweight and obese, having above median income and junior high education, and who are employed tend to have higher increases in BMI and overweight/obesity incidences. BMI and overweight/obesity incidence increases could partially be attributed to changes in physical activity, but more significantly to changes in food consumption. We observe an increase in food expenditure, along with all macronutrient indicators, salty foods, and prepared food sources.

The rest of this article is organized as follows. The next section describes the profile of both super apps and their expansion strategies. Section 3 details the data and statistical methods used in the empirical analysis. The results are presented in Section 4, followed by the discussion and policy implications in Section 5 and conclusion in Section 6.

2 Expansion of Super Apps in Indonesia

Currently, there are two largest super app providers in Indonesia. The first is Gojek, a national company founded in October 2010 and piloted with around 20 drivers using a call center basis. The initial concept was to connect informal motorbike riders in Indonesia with consumers; as these riders previously operated sporadically and often spent considerable time waiting for customers to find them (Azzuhri et al., 2018). Then, in January 2015, coinciding with Uber expansion, Gojek obtained seed funding to build a ridesharing application. Beyond the food delivery feature, Gojek offers a wide range of services, including transportation, logistics, and home-based services making their platform known as a 'super app' (Safira & Chikaraishi, 2022). By March 2018, the company had expanded to 107 districts in Indonesia (Figure 1). In 2021, Gojek merged with another large-scale e-commerce company in Indonesia, Tokopedia, creating the largest digital ecosystem with even wider services coverage, changing their company name to GoTo[1]. Currently, Gojek has expanded its services to Vietnam, Thailand, Singapore, and the Philippines.

[1] https://www.gotocompany.com/en/products/tokopedia

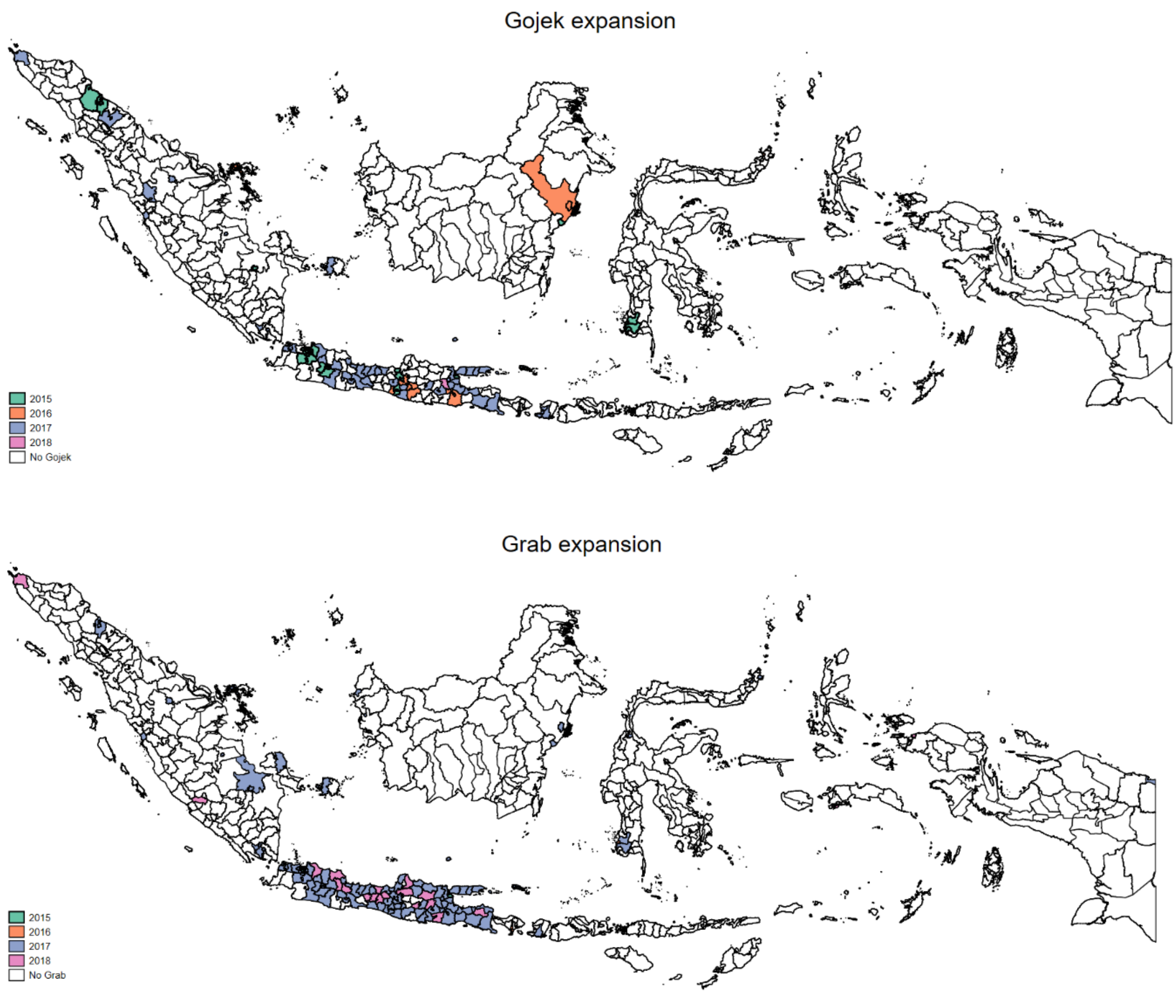

Figure 1 Expansion of digital platforms companies in Indonesia during 2015-2018

The second largest super app is Grab, a Malaysian company based in Singapore, which expanded its service to Jakarta, Indonesia's capital, in June 2014. In the beginning, Grab provided an app-based taxi-hailing service[2]. Upon their entry to Indonesia, they expanded their services to car ridesharing, motorbike ride hailing, and delivery services. Both companies have been in direct competition since their inception, rapidly expanding their services to districts in Indonesia. By the first quarter of 2018, Grab covers more than 148 districts (Figure 1), of which 97 districts overlap

[2] https://www.bbc.com/news/business-56967633

with Gojek. From 2017 onwards, Grab expanded its reach into more rural districts than Gojek (Figure 2).

During the first few months of the super apps launch, the highest demand for their services was related to food purchases (i.e., picking up, delivering, and driving the customer to restaurants). Gojek and Grab responded to this demand by launching a food delivery feature that connects stores and consumers in selected urban districts. This feature was released in April 2015 enabling consumers to order their food online from food vendors (i.e., restaurants, western fast food chains, local eateries, street food stalls) and get them delivered by bike riders. By then, consumers can see the properties of food (i.e., portion, content, price) through the application, thus simplifying the transaction process. The food available for delivery includes Western fast food (i.e., pizza, burger, sandwiches, deep fried dishes), prepared local dishes (i.e., rice dishes, noodle dishes, fried/grilled meat/chicken/fish, soups, etc.), snacks and dessert drinks, and ultra-processed foods (i.e., sausages, meatballs, nuggets, soft drinks). By the end of 2015, Gojek expanded its services to include partnerships with supermarkets and minimarkets allowing people to order staple food, fruits, vegetables, and meat products using their app. Grab only followed with supermarket partnership in 2019. In this study, both the impact of super app expansion and their food delivery feature will be examined.

Gojek and Grab highlight their contributions to Indonesia's economy. Based on several studies that they funded in recent years, both companies demonstrated significant contributions to the national economy, including a 2.8 % increase in Indonesia's GDP[3]. Gojek further showcased their

[3] Calculated from a study by Walandouw & Primaldhi (2021) and news piece in *CNN Indonesia*

contribution to economic development such as a reduction in district poverty by 0.32 p.p., a decrease in income inequality by 0.012 Gini points (4%), the creation of job opportunities for 1.7 million people (1.2% of Indonesia's working population), and linking up almost 1 million merchants (i.e., small-medium enterprises, supermarkets, and traditional markets). With more than 150 million users in 2019 and an average of 9.6 million rupiahs (more than US$ 676) in transactions per customer per annum[4], these contributions helped buffer economic shocks during the COVID-19 pandemic (Walandouw & Primaldhi, 2021). On the other hand, Yasih (2022) reported that these companies often exploit their workers with low pay and long working hours, which diminishes the well being of their workers. Despite the contradiction regarding the workers well being, very few studies have yet to see whether the presence of such companies plays a role in influencing the population's consumption and health outcomes.

[4] https://katadata.co.id/digital/startup/643e43ec9803e/tren-jumlah-pengguna-goto-gojek-dan-grab-siapa-paling-cepat

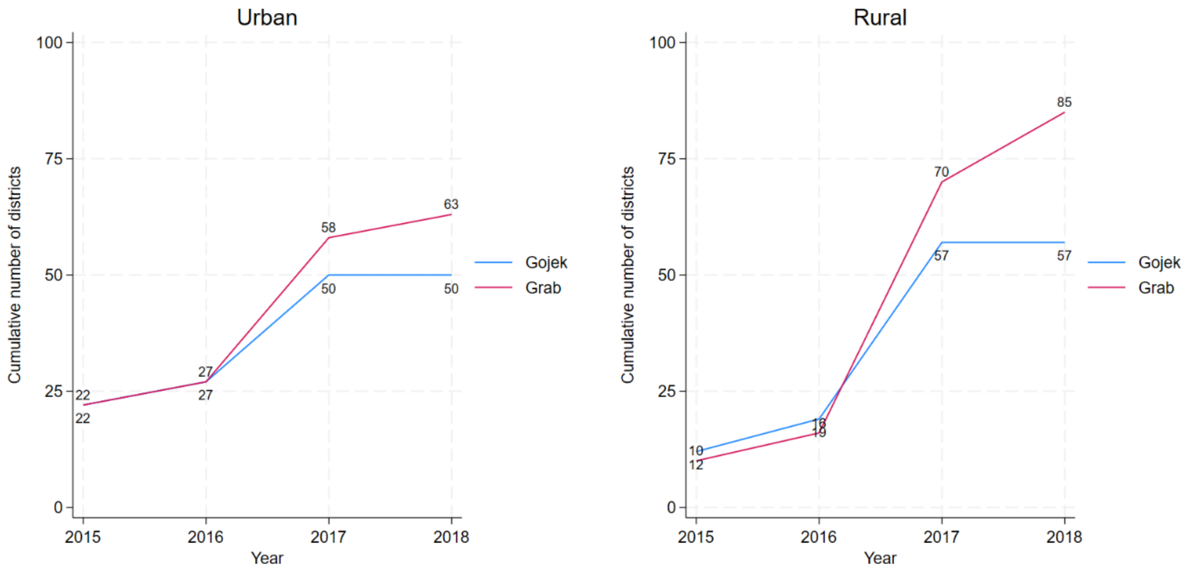

Figure 2 District expansion of digital platform services in urban and rural districts

3 Materials and Methods

3.1 Data

To examine the effect of the super app on anthropometric outcomes, we utilize the adoption time of the two largest digital platforms existing in Indonesia, Gojek and Grab, from 2015 to 2018 across 158 of the 497 districts (339 control districts) in Indonesia. This information is used to conduct a difference-in-differences analysis using the nationally representative *Riset Kesehatan Dasar* (Riskesdas) data to evaluate super apps' impact on nutritional outcomes. Riskesdas is a repeated cross-sectional survey conducted every few years to collect information on anthropometric measures and health information for more than 1,000,000 individuals and is representative at the district level. As dietary patterns take time to shift and consequently longer time to affect nutritional status, using the health outcomes data from the years 2013 (baseline) and 2018 (endline) would be sufficient to test if the long-term effect of super apps exists. The health dataset from the year 2007 is also used to conduct a placebo test, comparing the pre-treatment trends of outcomes between districts with and without super apps. This is done to ensure that any treatment effects observed are attributable only to the super app expansions and not to other factors. We aggregated the data of individuals aged 19-65 at the district level, forming panel data of 497 districts across the two periods.

To investigate the impact pathways, food consumption variables available in *Survei Sosioekonomi Nasional* (Susenas) are analyzed. Susenas, a repeated cross-section survey, provides information on household demographics, household expenditure, different food group consumption, food purchases outside the home, and other nutrient consumption for around 300,000 households annually. Given data availability, it is possible to utilize the yearly Susenas data from 2012 to 2018.

Household consumption data is aggregated at the district level to form a panel dataset covering 497 districts.

District-level information is collected to generate baseline district covariates from other data sources, such as *Potensi Desa* (Podes) and geospatial data. Podes is a village census conducted every three years collecting information on the livelihood, geographical information, infrastructure, and socioeconomic network of each village in Indonesia. The village-level information is aggregated at the district level to serve as covariates in the regression. Geolocation data is obtained from the *Badan Pusat Statistik* (Statistics Indonesia) containing the longitude and latitude data at the district level.

3.2 Key Variables

The main outcomes investigated in this study are the nutritional status indicators, specifically anthropometric measures such as BMI and waist circumference. BMI is calculated using an individual's w (weight in kilograms) and h (height in centimeters) using the following formula:

$$BMI = \frac{w}{h^2} \tag{1}$$

Using the BMI scores, an individual's nutritional status is defined using the following cutoffs: underweight if the BMI is below 18.5; overweight if the BMI is above 23 (Asian population cutoff) or above 25 (WHO cutoff, which is based on the Western population); obese if the BMI is above 27 (Asian population cutoff) or above 30 (WHO cutoff) (Tan, 2004). The Asian cutoff helps to ensure regional relevance as the Asian population tends to have higher risks for overweight and obesity at a lower BMI score. Meanwhile, the use of the WHO cutoff helps to interpret the results within a more globally recognized standard. We acknowledge that BMI has limitations in accounting for body fat and muscle mass composition, which may obscure the identification of overweight and obesity. Therefore, to corroborate the findings from BMI, we also use waist circumference measurements, taken one centimeter above the naval, for individuals aged 15 and above. In Asia, a waist circumference above 80 cm for females and 90 cm for males is categorized as central obesity, while for the Western population, the cutoff is above 84 cm for females and above 94 males (Obesity in Asia Collaboration, 2007; World Health Organization, 2000).

Physical activity and food consumption as additional health outcome measures are collected to investigate the impact pathways, as super apps might discourage active lifestyles and encourage unhealthy dietary habits. Here, the physical activity variables calculate the number of minutes that individuals spent doing heavy (i.e., lifting heavy objects, doing sports) and medium (i.e., cooking, walking) physical activity in the past week as a proxy to measure active lifestyles. The minimum time for moderate and heavy activity is 150 and 60 minutes per week to be categorized as healthy (WHO, 2020). We also analyze unhealthy food consumption using data from Riskesdas and detailed household macronutrient consumption from Susenas. Riskesdas collected data on the frequency of unhealthy food consumption in the past week, which includes sugar-sweetened food/drinks, fried food, grilled food, instant food, and caffeinated drinks. Meanwhile, Susenas collected detailed information on the amounts and expenditures for various food items and groups at the household level (own production and purchase) in the past week along with their protein, fat, carbohydrate, and calorie conversion. In Susenas, the prepared food consumption group is comprised of ready-made food (e.g., rice dishes, grilled meat/chicken/fish, noodle dishes, snacks), which households buy from outside the house, serving as a proxy for processed food consumption. We divide household macronutrient and food group expenditure by the number of individuals living in the household to obtain per capita food consumption indicators.

The main explanatory variables are the availability and launching date of Gojek and Grab with information on their food delivery services in 497 districts in Indonesia. For Gojek, the data was obtained from the official launching date information of cooperating districts directly from the company. Meanwhile, Grab and launching date/area of food delivery feature was obtained by manually tracking the news in local media outlets or social media.

3.3 Identification Strategies

To assess the super app's effect on nutritional outcomes, this study employs several difference-in-differences estimations using district-aggregated and individual-level data. We compare the nutritional outcomes of districts/individuals exposed to the platform starting from 2015 (treatment) with those that are not (control), both before and after the adoption period. Treatment is defined as districts with either Gojek, Grab, or both launched between January 2015 and March 2018. Districts that have neither Gojek nor Grab during the same period are treated as control groups. However, this study is not looking at the impact of each company separately as the aim is to see the effect of super apps in general. This approach assumes that the treatment and control districts had similar trends in nutritional outcomes before the platform's rollout, allowing any post-adoption differences to be attributed to the treatment. To validate the parallel trend assumption, a placebo regression is performed using nutritional outcomes prior to the baseline period, specifically comparing outcomes between treatment and control groups before 2015.

The effect of super apps on the nutritional status at the district level is estimated using the following model:

$$N_{d,t} = \beta_1 Tr_{dt} + \gamma_t + \alpha_d + \varepsilon_{dt} \quad (2)$$

In Equation (2), the subscript *d* denotes the district and *t* denotes the year of observation. $N_{d,t}$ represents outcomes (BMI, underweight, overweight, obesity, waist circumference) averaged at the district level. β_1 is the effect of digital platforms' presence on district-level outcomes. Tr_{dt} is the variable that equals one for districts that had at least one platform launched between 2015 and 2018, both during and after the initial launch of the platform, and zero otherwise. γ_t is a year fixed effect. α_d is the district fixed effect. ε_{idt} is the error term. Additionally, we tested the heterogeneity of the impact based on district characteristics, such as urban and rural status, GDP level, district development indicators, and super app service types (e.g., general vs. food delivery).

One of the main issues of our identification is whether the digital platform entry decision is correlated to consumption and nutrition indicators. While both companies' mission is to ensure as wide coverage as possible throughout Indonesia, this does not guarantee that other factors associated with consumption and nutrition were not associated with the super app's entry decision. To address this issue, we first estimate both companies' decision to enter a district using linear regressions exploring variables that have been previously explored in similar studies such as population size, economic status, average education level, and other socioeconomic variables (Berger et al., 2018; Hall et al., 2018). Afterward, the baseline covariates that predict both super apps' entry into a district and the trend in nutritional outcomes among control districts are incorporated in the regression to ensure a conditional parallel trend using a doubly robust estimator. While the unconditional difference-in-differences estimator is sufficient when parallel trend assumptions are met, the doubly robust approach provides a more conservative estimate. Additionally, we accounted for potential spillover effects, acknowledging that employment in digital sectors in Indonesia could lead to spatial spillover, with workers commuting and services extending to nearby districts depending on distance and road accessibility (Siregar, 2022). To address these issues, we conduct robustness tests by taking into account possible spillover by incorporating the distance matrix to test if neighborhood effect exists (Cerulli, 2017).

A doubly robust estimator utilizes covariates by combining inverse probability weighting (IPW) and outcome regression. The IPW approach generates analytical weights based on the inverse of the probability of super app entry at the district level, conditional on covariates. Outcome regression models the relationship between the outcome and treatment, adjusting for baseline covariates to create a counterfactual outcome. A doubly robust estimator combines both methods, ensuring consistent estimation even if either the IPW model or the outcome regression is misspecified (Sant'Anna & Zhao, 2020).

In addition to the district-level difference-in-differences analysis, this study also employs an individual-level analysis using a repeated cross-section estimator. This approach allows us to estimate the distributional effect on both platforms and its heterogeneous impact across different individual-level population groups. The following individual level regression model is used:

$$N_{i,d,t} = \beta_1 Tr_d + \gamma_t + \alpha_d + \varepsilon_{idt} \tag{3}$$

where the subscript *i* denotes the outcome, covariates, and error at the individual level. ε_{idt} is the error term that is clustered at the district level. Since the treatment is available at the district level and there is no information on individual usage of the services, our estimation measures the intent to treat effect at the individual level. The same control variables used in the district-level regression are included, with the addition of individual-level covariates such as education, socioeconomic status, gender, age, and employment. Individual-level analysis is conducted to assess digital platforms' effects on nutritional outcomes across different groups of individuals, categorized by welfare level, gender, age group, and education level. Additionally, this approach allows us to estimate super apps' effects across different quantiles of nutritional status using the unconditional quantile regression methodology (Firpo et al., 2009). Specifically, the sample is divided into equal n-th percentiles and applied the Recentered Influence Function (RIF) regression to create an unconditional analog of the BMI distribution. Then, the treatment effects on the RIF-transformed BMI are estimated using a difference-in-differences approach, adjusting for selection factors influencing digital platform entry into a district via inverse probability weighting (IPW).

To investigate the impact pathways of super app effects on nutritional outcomes, we look into several outcomes associated with changes in the food environment such as physical activity, unhealthy food consumption, food expenditure, and macronutrient consumption. The analysis for physical activity and unhealthy food consumption utilizes Riskesdas data using the model in Equation (2). As expenditure and food consumption data are available annually, it is possible to conduct a multiple period analysis (2012-2018) using a staggered difference-in-differences approach as specified in Equation (4). This is done by estimating a weighted average of all possible 2x2 difference-in-differences combinations across different periods within our samples (Callaway & Sant'Anna, 2021). The following staggered difference-in-differences model is used:

$$E_{d,t} = \sum_{k=t}^{T} \beta_k \, Tr_{d,t} + \gamma_t + \alpha_d + \varepsilon_{d,t} \tag{4}$$

Where $E_{d,t}$ represents expenditure and food consumption indicators. Parameter β_k indicates the difference in outcomes between districts with and without super apps before and after platform launching. From our data, t can start from 5 years before up to 3 three years after the first super app is launched at the district level. The before-launching period estimates depict the empirical test of parallel trend assumptions, while the after-launching estimates measure the dynamic effect of super apps on expenditure and food consumption up to three years after the baseline.

4 Results

4.1 The Nutrition Transition in Indonesia

From 2013 to 2018, the adult population in Indonesia experience a significant increase in overweight and obesity incidence. Using the Asian population standard BMI cutoff, 50% of the adult population in districts with super apps and 46% in districts without super apps were classified as overweight or obese in 2013, rising to 58% and 53% respectively by 2018 (see Table 1). This represents a 7-8 p.p. increase in overweight/obesity prevalence over five years (15.2% and 16% relative increase in districts without and with super apps). The increase is even more pronounced using the WHO cutoff, where in districts without the apps, overweight incidence rose from 27% in 2013 to 35% in 2018 (29.6% proportional increase), and in districts with the apps, from 31% in 2013 to 40% in 2018 (29% proportional increase).

Conversely, the incidence of underweight individuals slightly decreased by around 11% in both districts with and without super apps between 2013 and 2018. These patterns confirm the double burden of malnutrition hypothesis where the rate of overweight/obesity increase outpaces underweight reduction (Popkin et al., 2020; World Health Organization, 2016). Changes in food systems making unhealthy food more accessible and affordable, technological advancements reducing physical activity, and slow welfare improvement among the poor are some drivers of the nutrition transition in LMICs (Popkin et al., 2020).

Districts with super apps tend to have significantly higher overweight and obesity incidence (using both WHO and Asian cutoffs) over time compared to the districts without the platforms, indicating different levels of development across regions. Using the WHO cutoff, obesity rates increase almost twice as much within five years, indicating that BMI increases over time tends to affect the upper-end distribution. One example can be observed with the increase in obesity (WHO cutoff) prevalence gap between treated and control districts from 1.4 p.p. in 2013 to 2.4 p.p. in 2018. This finding suggests that factors such as super app expansions might contribute to the acceleration of overweight/obesity incidence increase.

Waist circumference measurement is also used to provide a more comprehensive obesity assessment. Our analysis shows a 17-18% (Asian cutoff) and 26-27% (WHO cutoff) increase in central obesity incidence over five years in control and treated districts. The findings on central obesity incidence confirm previous categorization of overweight/obesity using BMI measurement. It also reveals a strong correlation between overweight and central obesity incidence at the district level, with correlations of 80.67% using the WHO and 75.92% using the Asia cutoff. This indicates that BMI remains a reliable proxy for determining nutritional status in the Indonesian context.

Table 1 Nutritional status indicators among adults aged 19-65

	2013			**2018**		
	A. Control districts	**B. Treated districts**	**Difference**	**A. Control districts**	**B. Treated districts**	**Difference**
Overweight (Asia)	0.46	0.50	0.0403***	0.53	0.58	0.0455***
	(0.50)	(0.50)	(27.90)	(0.50)	(0.49)	(31.50)
Overweight (WHO)	0.27	0.31	0.0412***	0.35	0.40	0.0501***
	(0.44)	(0.46)	(31.59)	(0.48)	(0.49)	(35.81)
Obese (Asia)	0.15	0.18	0.0306***	0.22	0.26	0.0411***
	(0.36)	(0.39)	(28.83)	(0.41)	(0.44)	(33.83)
Obese (WHO)	0.06	0.07	0.0140***	0.09	0.12	0.0238***
	(0.23)	(0.26)	(20.07)	(0.29)	(0.32)	(27.45)
Underweight	0.09	0.09	-0.000366	0.08	0.08	0.000351
	(0.29)	(0.29)	(-0.44)	(0.27)	(0.27)	(0.45)
Central obesity (Asia)	0.29	0.33	0.0397***	0.34	0.39	0.0436***
	(0.45)	(0.47)	(30.11)	(0.47)	(0.49)	(31.58)
Central obesity (WHO)	0.19	0.22	0.0368***	0.24	0.28	0.0403***
	(0.39)	(0.42)	(32.03)	(0.43)	(0.45)	(32.22)
Observations	431,275	166,745	598,020	419,948	167,593	587,541

Note: Sampling weights are applied in the estimations. Calculated using Riskesdas data. Difference was tested using t-tests.

4.2 Determinants of Super Apps Entry

Understanding factors correlated with the entry decision of Gojek and Grab is important to address potential endogeneity issues. Factors affecting Gojek’s and Grab's entry may also drive the changes in nutritional outcomes. This section aims to identify factors associated with super app entry decisions to be incorporated as covariates in the main estimation. All the independent variables are measured in standard deviation to allow for magnitude comparison.

Table 2 shows super apps’ entry into a district is strongly predicted by population size in urban areas, median working age, education, and being in the Jawa and Bali islands (See Table 2). For Gojek, there are also other factors predicting their entry such as employment in the industry, internet access coverage, and growing districts (trend in population). While super apps’ entry in developed countries mainly correlates with population size (Berger et al., 2018; Hall et al., 2018), factors such as urbanization, education, employment, and age are also influential in Indonesia. This finding highlights the difference in the underlying business operation models where super app expansions in LMICs not only focus on the most populated areas but also those with economic prospects. In the main estimations, factors associated with super app entry decisions will be accounted for to tackle the endogeneity issues by incorporating them using a doubly robust estimator.

Table 2 Linear regressions predicting the entry of digital platforms into districts

	(1) *Gojek*	*(2)* *Grab*	*(3)* *All platforms*
Log(population)	0.12***	0.11***	0.12***
	(0.02)	(0.02)	(0.02)
Percent population in urban areas	0.10**	0.14***	0.14**
	(0.04)	(0.04)	(0.04)
Trend in population (growth rate)	0.02***	0.01	0.01
	(0.01)	(0.02)	(0.02)
Percent population with internet	0.08**	0.07*	0.06
	(0.04)	(0.04)	(0.04)
Percent with senior high degree and above	-0.07**	-0.09***	-0.09**
	(0.03)	(0.03)	(0.03)
Percent working in industry	0.08***	0.04**	0.05**
	(0.02)	(0.02)	(0.02)
Percent working in service	0.05	0.06	0.06*
	(0.03)	(0.03)	(0.04)
Median working age	0.03*	0.06**	0.06***
	(0.02)	(0.02)	(0.02)
Percent HH with motorcycle/car	-0.05**	-0.03*	-0.03*
	(0.02)	(0.02)	(0.02)
Median income	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.02)
Regional gas price	0.03**	0.02*	0.02*
	(0.01)	(0.01)	(0.01)
Log(km distance from district to provincial capital)	-0.04**	-0.05**	-0.05**
	(0.02)	(0.02)	(0.02)
# of establishments per 1000 population	0.01	-0.00	0.00
	(0.01)	(0.01)	(0.01)
Districts in Jawa and Bali islands (dummy)	0.06**	0.09***	0.07**
	(0.02)	(0.03)	(0.03)
Constant	0.27***	0.31***	0.32***
	(0.01)	(0.01)	(0.01)
Observations	446	487	497
R-squared	0.630	0.640	0.628

Note: *** p<0.01, ** p<0.05, * p<0.10. Data on Gojek entry was gathered through Gojek's liaison and Grab was collected manually using web searches. Data on population, education, age, employment, ownership of phones, internet, vehicles, and regional gas prices was collected from Susenas 2012. Distance to the province capital was calculated using Euclidean distance from the district centers. The number of establishments was collected using Podes 2011 and 2014, which include small stores, minimarket, traditional markets, and restaurants in the district. The trend in population calculates the relative annual growth of the district population from year 2012-2014.

4.3 The Effect of Super Apps on Nutritional Outcomes

4.3.1 Placebo tests

Before going to the main estimation, this sub-section aims to identify the presence of pre-treatment differences using the model in Equation (2) by comparing nutritional outcomes in 2007 and 2013 among districts that eventually have super apps and those that do not. Figure 3 shows no significant difference for most of the nutritional outcomes in the pre-treatment period, except for overweight incidence, which tends to be lower in treated districts compared to the control districts in the pre-treatment period. We address this issue by including the covariates ensuring conditional parallel trend in the pre-treatment period (Figure 3, Panel B). We also find no significant difference in BMI scores, waist circumference, obesity incidence, and underweight between districts that eventually are treated and those that are not, before super apps launched in 2015.

Since most of the nutritional outcomes indicators between districts with and without super apps evolve in the same pattern, any difference observed post-treatment could be attributed to super apps presence rather than the pre-existing difference between the groups. However, to account for potential confounding factors affecting super app expansions and the nutrition transition, we incorporate the baseline covariates that predict super apps' entry into a district and the trend in nutritional outcomes among control districts to ensure a conditional parallel trend. The covariates included in the regressions are the proportion of people residing in urban areas, having higher education, employment, and the median working age. In addition to that, other factors that would affect obesity incidence at the district level are also incorporated such as district GDP, the availability of community health centers, hospitals, access to clean water and toilets, gender ratio, and health insurance (Rachmi et al., 2017).

4.3.2 Main results

This sub-section focuses on the estimation of the treatment effect of super apps on various nutritional outcomes at the district level using the model in Equation (2). Before incorporating covariates, districts with super apps have higher obesity incidence (WHO cutoff) by up to 0.8 p.p. compared to districts without super apps (Figure 3, Panel C, green tick marks). After incorporating covariates, the findings suggest that super apps' presence at the district level led to significantly higher population BMI scores and overweight/obesity incidences. BMI score increased among districts with super apps by 0.16 (Figure 3, Panel A), followed by increases in overweight and obesity (WHO cutoff) by around 0.9-1.4 p.p. (Figure 3, Panel C) compared to the control districts. These results are more robust and higher in magnitude than the results from the unconditional estimator. This means that without considering baseline covariates that influence super app entry and the evolution of outcomes, the true effect of super apps on nutritional status tends to be underestimated. Moving forward, we will refer to the doubly robust estimation results.

To corroborate our previous findings, we also estimate the treatment effect using different cutoffs and indicators. The findings suggest no significant associations when we determine the nutritional status using the Asian cutoff, which is lower than the WHO cutoff. This indicates that the effects of super apps are more pronounced among individuals with higher BMI scores, as classified by the WHO criteria. Despite the larger standard error in estimating waist circumference, the magnitude and direction of the coefficient are consistent with our BMI findings. Districts with super apps show a 0.36 cm higher circumference compared to control districts (Figure 3, Panel A). However, this increase does not correlate with significant increases in central obesity incidence (Figure 3, Panel B and C). Regardless, the direction of the relationship is consistent with our findings on BMI and obesity and further supports our hypothesis that super apps are associated with increased overweight and obesity prevalence in LMICs.

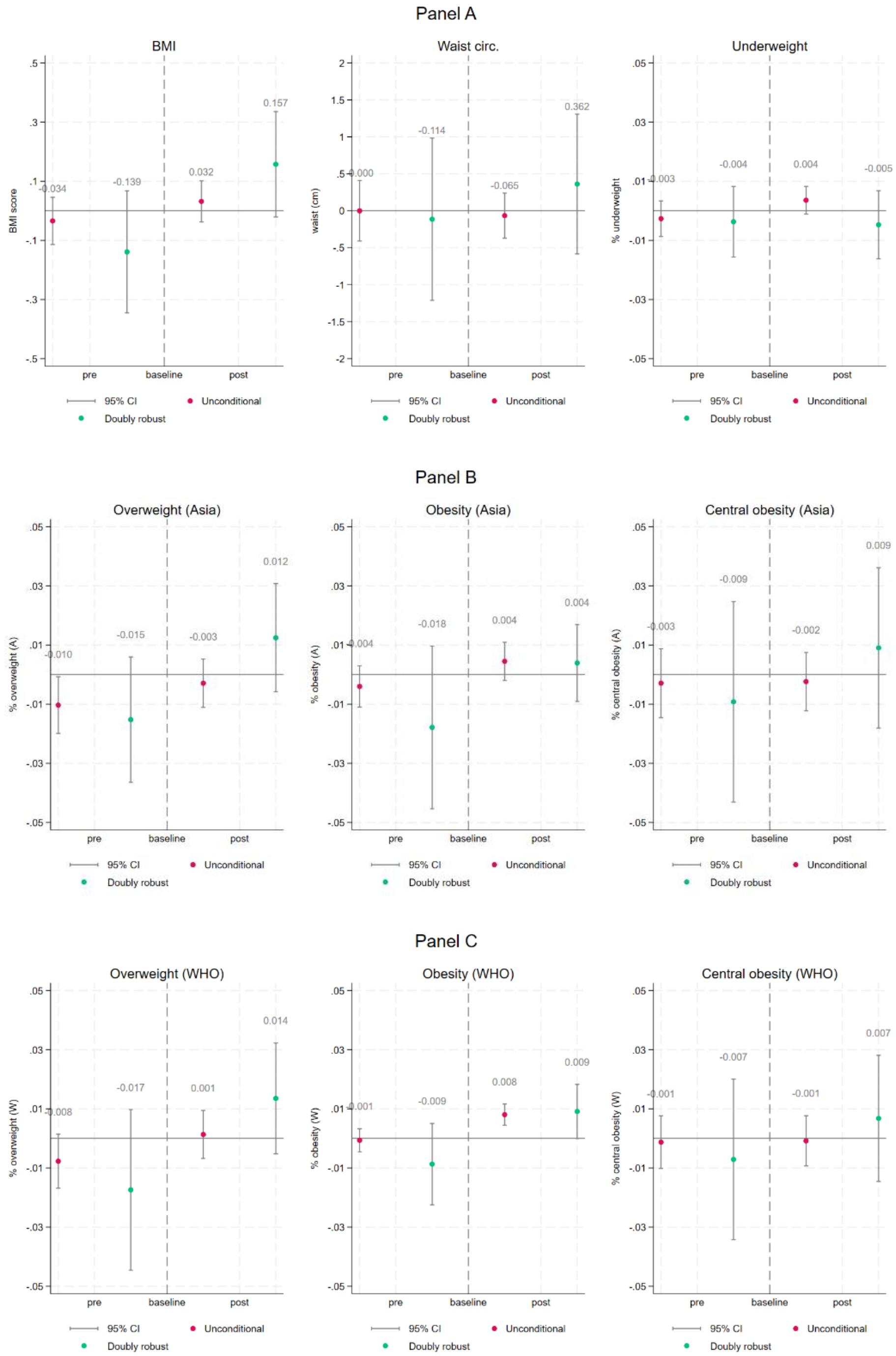

Figure 3 The effects of super apps on BMI and nutritional status

Note: Coefficients with 95% confidence intervals are shown. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2007, 2013, and 2018 data. Post-treatment period compared Riskesdas 2018 and 2013 data and pre-treatment period compared Riskesdas 2007 and 2013 data. Estimated using unconditional and doubly-robust difference-in-differences method. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, median working age, access to clean toilet and water, access to health insurance, health care availability, number of establishments, and male-female ratio.

4.3.3 Heterogeneous Effects by District Characteristics

Super apps typically enter districts with higher urbanization and established technological infrastructure (i.e., internet access and mobile phone ownership). Gojek and Grab prioritized their initial entry to metropolitan cities in Indonesia, while subsequent entry focused on areas with higher population numbers and urbanization. Residents in metropolitan, urban, and more affluent areas are more likely to use online services, leveraging available infrastructure to avoid traffic jams and save time. Meanwhile, residents of rural and less affluent areas might have limited access to online services due to a lack of road or internet infrastructures (Hall et al., 2018). These differences in service availability based on district characteristics can influence how people utilize digital platform services. Therefore, conducting heterogeneous treatment effects analysis based on district characteristics could reveal varying relationships.

Table 3 shows that BMI score and overweight/obesity incidence are significantly higher in the cities and more affluent districts. This confirms our hypothesis that digital platforms have a stronger effect in better-off areas. In the cities, digital platforms have significant effects on all nutritional outcomes. The presence of super apps in the cities is associated with a higher 0.6 BMI score and 1.8 cm waist circumference than urban controls (Table 3). This is followed by increases in overweight, obesity, and central obesity incidences (all cutoffs) in cities by around 1.7 p.p. – 5.6 p.p. These changes account for more than 10% relative increases in overweight and obesity incidences in the cities compared to the baseline period. Additionally, underweight incidence among adults is significantly lower in cities with super apps, indicating that the effect of super apps in the cities is equally increasing across BMI distribution and could potentially help with reducing undernutrition issues. Increases in BMI scores and obesity incidences are also observed among districts with above median GDP (compared to lower GDP) confirming our findings on super apps having more influence among larger and more affluent districts.

However, the increase in BMI and overweight/obesity incidence is not only driven by the significant increases in urban and more well off areas. After excluding metropolitan and early adopters districts, which tend to be bigger cities, super apps presence in the smaller districts is still associated with higher obesity incidences compared to the control groups. Among late-entry and non-metropolitan districts, super apps are associated with up to 1 p.p. increase in obesity incidence. This finding indicates that, despite the smaller effect, super apps still pose negative externalities on weight gain in less affluent areas.

Additional heterogeneous treatment effect analysis is conducted to determine whether the significant results were driven by the super apps overall or solely by the online food delivery feature. This involved comparing districts with the specific online food delivery feature available by 2018. Table 3 shows that super apps' effects on BMI, overweight, and obesity disappear when not taking into account the food delivery features. Only the obesity (WHO cutoff) indicator is significantly higher in districts with super apps but without the food delivery feature compared to districts without super apps. This finding shows that the significant effect of the super app on most nutritional outcomes is mainly driven by the availability of food delivery features within the app. The findings in super app districts with online food delivery services are similar to those in cities, confirming an overlap between city characteristics and regions where super apps were more commonly established during super apps' early years.

Table 3 Heterogeneous treatment effects of super apps on BMI, waist circumference, and nutritional status

	All adults	*Cities*	*Regen-cies*	*GDP above median*	*GDP below median*	*Excl. metro-politan*	*Excl. early adopters*	*With food delivery*	*Without food delivery*
BMI	0.157*	0.596***	0.103	0.177*	0.05	0.144*	0.146	0.569***	0.096
	(0.091)	(0.182)	(0.067)	(0.092)	(0.138)	(0.085)	(0.09)	(0.195)	(0.069)
Overweight (A)	0.012	0.056***	0.009	0.013	-0.003	0.011	0.011	0.059***	0.005
	(0.009)	(0.014)	(0.007)	(0.01)	(0.016)	(0.009)	(0.009)	(0.018)	(0.007)
Overweight (W)	0.014	0.042***	0.005	0.012	0.019	0.012	0.013	0.046**	0.01
	(0.01)	(0.016)	(0.012)	(0.01)	(0.019)	(0.009)	(0.01)	(0.021)	(0.009)
Obesity (A)	0.004	0.017	-0.001	0.004	0.011	0.004	0.004	0.015	0.003
	(0.007)	(0.014)	(0.01)	(0.006)	(0.015)	(0.006)	(0.006)	(0.015)	(0.007)
Obesity (W)	0.009*	0.022***	0.007	0.009**	0.008	0.009**	0.009*	0.021**	0.008*
	(0.005)	(0.008)	(0.004)	(0.004)	(0.009)	(0.004)	(0.005)	(0.009)	(0.005)
Underweight	-0.005	-0.032***	-0.006	-0.009	0.013	-0.004	-0.004	-0.027***	-0.001
	(0.006)	(0.012)	(0.007)	(0.006)	(0.013)	(0.006)	(0.006)	(0.008)	(0.006)
Waist circum-ference	0.362	1.8***	-0.048	0.52	-1.08*	0.322	0.283	3.209***	-0.104
	(0.483)	(0.652)	(0.351)	(0.429)	(0.648)	(0.422)	(0.446)	(1.04)	(0.342)
Central obesity (A)	0.009	0.041***	-0.004	0.01	-0.027	0.008	0.007	0.084***	-0.003
	(0.014)	(0.015)	(0.018)	(0.013)	(0.02)	(0.012)	(0.013)	(0.032)	(0.012)
Central obesity (W)	0.007	0.032**	-0.005	0.008	-0.01	0.006	0.005	0.061**	-0.001
	(0.011)	(0.013)	(0.016)	(0.01)	(0.02)	(0.01)	(0.011)	(0.026)	(0.01)
No. Obs	994	196	798	498	496	988	952	760	912

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2013, and 2018 data. Overweight and obesity indicators were estimated using the Asian and WHO cutoff. Estimated using doubly-robust difference-in-differences method. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, median working age, access to clean toilet and water, access to health insurance, health care availability, # of establishments, and male-female ratio.

4.3.4 Robustness Tests

Given that super app drivers and riders might come from nearby control districts or that services could extend to these areas if road infrastructure is adequate, we anticipate some spillover effects. Therefore, assuming that geographical distance among districts could capture the spillover effect, we incorporate the district Euclidean distance matrix to create an Omega matrix[5] where control districts closer to treated districts have higher weight than those further away. This allows us to account for the potential influence of neighboring districts by incorporating the Omega matrix as an analytical weight in the regression. The average treatment effects (ATEs) are calculated with and without the weight and then the two ATEs are subtracted to assess the potential spillover effects. A Wald test is then applied to test the significance of the difference in ATE estimates, indicating the presence of neighborhood effects if statistically significant.

The findings suggest no significant neighborhood effects for most of the nutritional outcomes. However, super apps' effect on obesity (WHO cutoff) prevalence tends to be underestimated by 5.65% when not taking into account the neighborhood effects (Online Appendix Table A1). While we acknowledge the possibility of spillover of treatment into the nearby control districts affecting obesity incidence of control districts, the magnitude of the bias is too small to affect our overall estimation.

4.4 Distributional and Heterogeneous Effects by Individual Characteristics

District-level aggregated analysis shows that super apps have a greater impact on obesity than on overweight incidence, indicating that these platforms tend to have more effect among those in

[5] Matrix omega is the *N x N* weighting matrix expressing the distance between district *i* and *j* which only has an impact when unit *i* is not being treated (Cerulli, 2017)

the upper BMI distribution. To test this hypothesis further, an individual-level quantile regression difference-in-differences analysis is performed. Figure 4 illustrates the results. The analysis shows that super apps presence at the district level is associated with increased BMI scores among those categorized as overweight and obese using both Asian and WHO cutoffs, with a more pronounced effect starting at the 40th percentile and above. The effect of the super app is also increasing as a person's BMI score increases, indicating that those who are already unhealthy are affected the most compared to those with healthier weight.

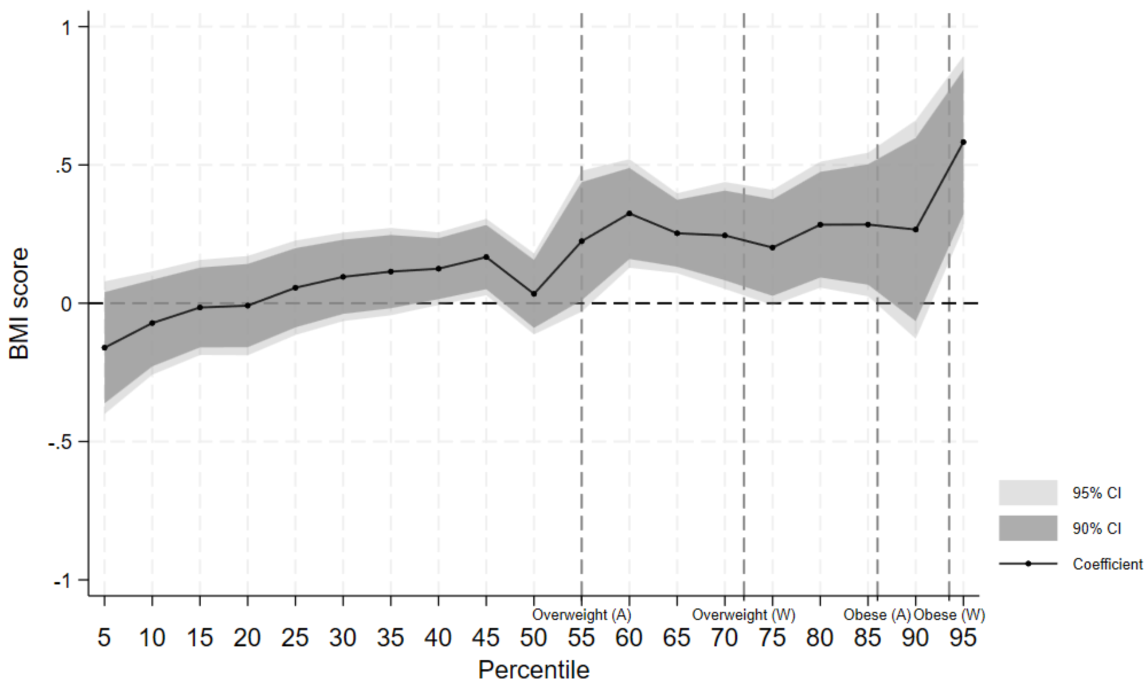

Figure 4 The effects of super apps on BMI across distribution

Note: Coefficients with 95% and 90% confidence intervals are shown. Unconditional quantile regression (UQR) of individual-level data, estimated using inverse probability weighting (IPW) method. The overweight and obesity cutoff was determined using the Asian (A) and WHO (W) cutoffs. IPW was estimated by re-weighting treatment allocation at the district level using variables such as population, GDP, employment, median working age, access to internet and vehicles, regional gas price, and location in Jawa and Bali. Additionally, individual level variables such as sex, age, education, employment, and socioeconomic status are incorporated.

Individual-level data allows us to conduct a heterogeneous treatment effects analysis using individual characteristics to measure intent-to-treat, assuming that all individuals within the same treatment districts might be affected regardless of super app usage. We conduct repeated cross-section difference-in-differences using the doubly robust estimator as specified in Equation (3). The sample was divided based on gender (male vs. female), per capita income level (below and above the median), having graduated junior high school and above, being employed, and age group. The findings show that super apps presence at the district level is associated with increased BMI and overweight/obesity among individuals with higher income, employment, and productive ages (Table A2 in Online Appendix). These findings further confirm the market segmentation of super apps among more affluent individuals, which might explain why their effects on nutritional outcomes are more prominent among these population groups.

4.5 Impact Pathways

Within the personal domain of the food environment, an increase in BMI among adults is likely when the energy consumed exceeds the energy spent. This imbalance can occur when individuals consume more calories than they do burn, due to either higher food intake or insufficient physical activity. Hence, to explain the nutrition transition trends among districts with super apps, we investigate changes in physical activity and food consumption associated with the platforms' expansion. This approach utilizes the information on physical activity and individual food consumption frequency from the Riskesdas data and detailed food consumption information from Susenas data.

We conduct a difference-in-differences analysis using the doubly robust estimator on the aggregated district-level physical activity time and the consumption of unhealthy food groups in the past week. The findings indicate that super apps have no significant effect on an individual's heavy and moderate physical activity (Table A3 Online Appendix). On the other hand, we find a higher frequency of unhealthy food consumption among super app districts. The consumption of salty foods in treated districts significantly increased by 3.5 p.p. compared to the control district (Table A3). While changes in physical activity levels might partially explain the BMI increase associated with super apps, the rise in unhealthy food consumption appears to play a more significant role in driving this effect.

The Riskesdas data provides insights into changes in consumption behavior but is limited in detailing the intensity of these changes. Additionally, it also lacks a grainy detail in household consumption patterns. To understand the magnitude of super apps' impact on consumption patterns, detailed consumption data from Susenas is used. This allows us to examine more clearly quantity changes in food expenditure and macronutrient consumption.

Using model Equation (4), we compare the expenditure and detailed food consumption variables of districts with and without super apps across multiple years of treatment period. We first show the parallel trend for the consumption data using pre-treatment data before the super app launched in 2015. Figure 5 shows that across multiple years before super apps launched, the average per capita food expenditure between districts with and without super apps followed the same pattern indicating no pre-treatment difference between the two groups. After the first year of the platform's launching (t1), the food expenditure (in log and real term) starts to increase and keeps on increasing yearly as the platforms expand their coverage. Among districts with super app operating for more than 2 years, per capita food expenditure could increase by up to 5.5%, which is approximately Rp 48,600 (US$ 3.42) per week (Figure 5).

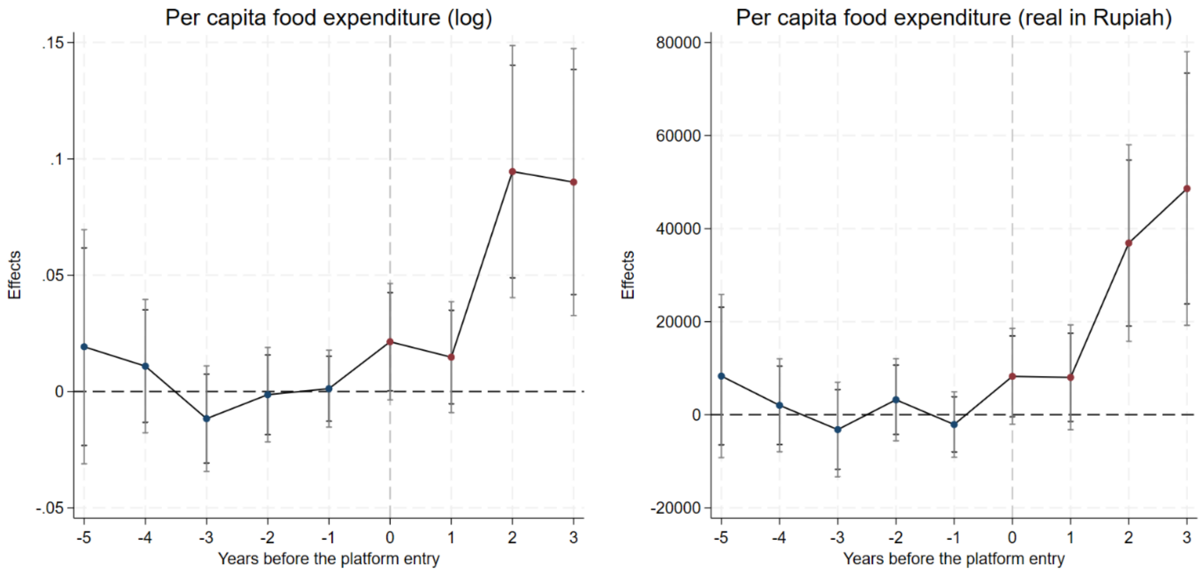

Figure 5 The staggered effects of super apps on total and food expenditures

Note: Coefficients with 95% and 90% confidence intervals are shown. Variables are aggregated at the district level from the Susenas 2012-2018 data. Estimated using staggered difference-in-difference method. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, and median working age. 1 US$ = Rp 14,196

We further explore the effect of super apps on different types of expenditure and macronutrient indicators between 2012 and 2018. In this survey, household overall expenditure also becomes a proxy for household income as income data is difficult to collect due to the high informality of employment in Indonesia. The findings show that digital platforms' presence at the district level increases the average per capita overall and food expenditure as well as calorie and fat consumption (Table 4). Per capita expenditure also increases by around Rp 72,117 (US$ 5.08) per week (8.4 %), indicating improved welfare among the population in districts with super apps. Additionally, food expenditure among districts with these platforms rose by around Rp 25,447 (US$ 1.79) per capita (6.3%) compared to districts without the platforms. The results also show an increase of around 1.5%-4% in calorie, protein, fat, and carbohydrate consumption among super app districts. These increases in consumption indicators might reflect both a rise in demand for consumption and improved welfare among the gig workers and associated food businesses.

Table 4 The effects of super apps on weekly food expenditure and macronutrient

Variable name	***Mean***	***Doubly-robust DiD***
Per capita expenditure (log)	13.38	0.047***
		(0.015)
Per capita food expenditure (log)	12.74	0.055***
		(0.014)
Per capita expenditure (real in Rupiah)	861,362	72,117.02***
		(19,542.8)
Per capita food expenditure (real in Rupiah)	401,616	25,447.37***
		(6,332.259)
Per capita calories (kcal)	2,073	31.379*
		(18.953)
Per capita protein (gram)	61.30	1.537**
		(0.716)
Per capita fat (gram)	53.40	2.116**
		(0.896)
Per capita carbohydrate (gram)	305.96	5.502*
		(2.966)
Total observations	994	

Note: *** p<0.01, ** p<0.05, * p<0.10. ǂ calculated for per capita in households. Estimations are calculated using doubly robust difference-in-differences methods. Variables are aggregated at the district level from Susenas 2012 and 2018 data. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, and median working age. 1 US$ = Rp 14,196

Table A4 in the Online Appendix analyzes food consumption patterns by examining expenditure, macronutrient content, and household dietary diversity scores to determine if certain food groups are more affected by super app presence. The findings show that the presence of super apps is associated with increases in expenditure on fruit (19.4%), meat (10.5%), and prepared food (9.4%) among super app districts compared to districts without the apps. While the increase in prepared food consumption is expected due to the nature of the majority of food products offered within the platform, the increases in fruit and meat could be seen in a positive light that these platforms could facilitate more nutritious food consumption.

5 Discussion

This study examines the impact of super apps providing food delivery and other services on nutritional status and food consumption in Indonesia, focusing on the district-level expansion of two major companies, Gojek and Grab, from 2015-2018. We compare health and nutrition outcomes between districts with and without these digital platforms. Our findings reveal three key points. First, super apps contribute to increased BMI scores and a higher incidence of overweight and obesity, specifically when an online food delivery option is integrated into the app. Second, the effects are more pronounced among those who are already overweight/obese, those who are educated and employed, and younger age groups. Third, changes in the personal domain of the food environment associated with super apps, likely contribute to the increased consumption of unhealthy foods, potentially explaining the observed increase in BMI and adverse effects on nutritional status. The findings show an increase in the consumption of unhealthy food groups, correlating with higher food expenditure, macronutrient intake, and prepared food consumption.

Our findings are consistent with existing research on the negative externalities of technology use in the food system, particularly in terms of the nutrition transition in LMICs. Digital platforms that facilitate food purchases, deliveries, and other daily services are associated with an increased risk of overweight and obesity. The availability of these services at the district level may contribute to a 10% relative increase in the incidence of overweight and obesity over time. While earlier research has primarily focused on identifying the user characteristics of food-related digital platforms, such as their demographic and behavioral characteristics (Dana et al., 2021; Dominici et al., 2021; Keeble et al., 2021, 2022), our study extends this scope by examining the broader population and individual level health effect of such platforms on the changes in nutritional status. It is not just that the users of these platforms are more likely to engage in unhealthy eating behaviors (e.g., being overweight, obese); the presence of this platform at the district level increases the risk of previously healthier individuals becoming overweight or obese. Our results differ from Keeble et al. (2021), who found no correlation between online food delivery and body weight among adults. This difference can be attributed to their narrow study timeline of two months, which may have been insufficient to observe significant changes in BMI.

As the expansion of such services often prioritizes market size, the effect of super apps on nutritional outcomes is likely more prominent in more urban and better-off areas. We find that treatment effect heterogeneity of super apps on overweight/obesity tends to be significantly higher in cities compared to regencies and in higher vs. lower GDP districts. Higher food networks, choice availability, better road infrastructures, and internet connectivity could lead to the greater use of digital platforms in more urban and economically advantaged districts (Hall et al., 2018).

At the individual level, we also confirm this hypothesis. The effect of super apps on BMI, overweight, and obesity is more prominent in urban areas and among those who are already overweight/obese and more affluent, exacerbating malnutrition among adults. Overweight and obesity risks associated with super apps tend to increase more for younger and better-off individuals. These findings are aligned with previous studies showing that digital services are more commonly used by affluent and younger populations who prefer convenience and affordability in their daily life (Meemken et al., 2022; Safira & Chikaraishi, 2022; Maimaiti et al., 2018). Younger adults are more susceptible to obesity due to an increase in welfare, followed by the consumption of unhealthy food and sedentary lifestyles due to their work commitments and internet exposures

(Michelle et al., 2024; Poobalan & Aucott, 2016), which can be worsened by super apps presence. This finding is concerning as it indicates that super apps can negatively affect the health of those in the productive age group and increase their risk of having chronic health issues.

This study also investigates the impact pathways of super apps on nutritional outcomes. We find that increased accessibility of a wider variety of foods, including unhealthy and prepared food options through these platforms likely contributes to the rise in BMI and overweight/obesity incidence. Through food consumption indicators, the findings indicate an increase in commercially prepared food consumption. These findings align with previous studies indicating that food-related digital platforms could exacerbate access to energy-dense and processed food as the majority of food within this platform can be categorized as unhealthy (Bennett et al., 2024; Horta et al., 2022; Granheim et al., 2021). Additionally, the consumption of delivery or takeout food is associated with lower food quality (high energy, fat, sodium, and sugar) and increased calorie consumption (Meemken et al., 2022), increasing the risk of overweight and obesity among adults. While other studies suggest that super apps encourage a sedentary lifestyle, our findings do not provide strong evidence to support this claim. There may be a reduction in physical activity associated with food preparation and cooking due to the super apps. However, since our indicators do not measure physical activity time by activity types separately, it is not possible to observe specific changes in time use, which provides avenues for potential research in the future.

On the contrary, our findings suggest that super apps have some effects that might help improve the nutrition transition. Super apps are associated with a decrease in underweight incidence in the cities, as well as an overall increase in food expenditure and the consumption of macronutrients, meat, and fruit. Our findings also indicate the income effect of super apps through the increase in overall expenditure among the population. This finding is consistent with previous studies showing that gig workers experience an increase in income and welfare improvement (Berger et al., 2019; Walandouw & Primaldhi, 2021). The increased food consumption among districts with super apps is also consistent with previous studies indicating that digital platforms have the potential to improve dietary diversity, especially in food deserts area outcomes (Brandt et al., 2019; Bennett et al., 2024). Easy access to diverse food networks and improved welfare among workers and businesses could improve households' food security and nutrition.

The findings from this study contribute to the niche literature on the effects of digital platforms on welfare and have significant public policy implications for the regulation of these platforms. Currently, super apps operate with minimal government oversight, but our findings suggest that regulatory intervention may be necessary (Bennett et al., 2024; Brouwer et al., 2021). Requiring digital platforms to provide nutritional information, such as calorie, fat, sugar, and protein content, through labeling or branding, and regulating the advertisement of junk or fast food could better inform consumers about their food choices. Additionally, restricting pricing strategies (i.e., promotion, discount, price reduction for bulk purchases) on certain food groups, such as those high in sugar, fat, or highly processed, might also help curb the excessive promotion of unhealthy products.

It is also worth noting that super app usage worldwide has surged globally since the COVID-19 pandemic, driven by lockdowns and quarantine mandates, which have normalized the consumption of food away from home (Meemken et al., 2022). Health policies must prioritize the younger population, who are more susceptible to the nutrition transition due to the postpandemic socioeconomic and cultural shifts (Michelle et al., 2024). Further research is needed to identify the root causes of malnutrition among vulnerable groups and to assess the long-term impact of super apps on dietary habits and nutritional outcomes, especially in LMICs.

While super apps present some negative health externalities, they also offer potential benefits, such as reducing underweight incidence and promoting more diverse food consumption. Currently, the private sector's contribution to addressing malnutrition is minimal, but there is significant potential for involvement. Encouraging super apps to connect traditional markets, supermarkets, and farmers directly could improve access to a more diverse diet (Liu et al., 2024; Shen et al., 2023). Additionally, offering ready-to-cook meal packages could help users save time while preparing healthier meals. Such efforts could easily be integrated into digital platforms, enabling consumers to make healthier choices while sustaining business growth.

6 Conclusion

This study aims to assess the impact of super apps on nutritional outcomes among adults using the expansion of mobile applications that offer food delivery, ridesharing, and other daily services. The findings suggest that the presence of super apps is associated with higher BMI and obesity incidences, especially in urban areas, among younger and more affluent individuals. The increase in overweight/obesity could be explained by the increase in unhealthy and prepared food consumption. Given the significant expansion of super apps in LMICs, more efforts need to be made to involve them in combating malnutrition associated specifically with these platforms' usage. While super apps seem to contribute negatively to the nutrition transition in LMICs, they also have the potential to mitigate and reverse the negative impact given the right policy approach and framing.

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8 Appendix

Table A1 Spillover effects of super apps on nutritional outcomes: Incorporating neighborhood influences

Outcome	*ATE no neighborhood*	*ATE neighborhood*	*Wald's test*	*Bias*	*% Bias*
Body mass index (BMI)	0.032	0.024	0.10	0.00805	25.20
	(0.043)	(0.044)			
Central obesity (Asia cutoff)	-0.002	-0.006	0.23	0.00386	-163.05
	(0.006)	(0.006)			
Central obesity (WHO cutoff)	-0.001	-0.003	0.61	0.00261	-313.90
	(0.005)	(0.005)			
Obesity (WHO cutoff)	0.008***	0.008***	0.01	0.00045	5.65
	(0.002)	(0.002)			
Obesity (Asia cutoff)	0.004	0.003	0.29	0.00139	30.98
	(0.004)	(0.004)			
Overweight (WHO cutoff)	0.001	0	0.18	0.00143	108.13
	(0.005)	(0.005)			
Overweight (Asia cutoff)	-0.003	-0.004	0.67	0.00097	-33.33
	(0.005)	(0.005)			
Underweight	0.004	0.004	0.98	0.00002	0.69
	(0.003)	(0.003)			
Waist circumference	-0.065	-0.123	0.58	0.05756	-88.21
	(0.181)	(0.187)			

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2013, and 2018 data. Overweight and obesity indicators were estimated using the Asian and WHO cutoff. Estimated using neighborhood effect approach. Wald's test was used to test if the neighborhood effect exists and if it significantly biases our estimation. We include controls that potentially effect results heterogeneity such as GDP per capita and employment.

Table A2 The effects of super apps on BMI and nutritional status: Heterogeneity Analysis using individual characteristics

Analysis results	*Σ districts*	*BMI*	*Overweight (Asia)*	*Overweight (WHO)*	*Obese (Asia)*	*Obese (WHO)*	*Underweight*	*Waist*	*Central obesity (Asia)*	*Central obesity (WHO)*
All sample	1,175,088	0.157*	0.012	0.014	0.004	0.009*	-0.005	0.362	0.009	0.007
		(0.091)	(0.009)	(0.01)	(0.007)	(0.005)	(0.006)	(0.483)	(0.014)	(0.011)
Income below median	541,855	0.114	0.01	0.012	0.004	0.007	-0.007	0.453	0.012	0.02
		(0.11)	(0.011)	(0.011)	(0.009)	(0.005)	(0.007)	(0.507)	(0.014)	(0.013)
Income above median	633,233	0.248	0.03*	0.024	0.005	0.009	-0.006	0.716	0.016	0.009
		(0.166)	(0.017)	(0.019)	(0.011)	(0.006)	(0.007)	(0.577)	(0.021)	(0.018)
Male	560,048	0.171	0.02	0.015	-0.002	0.001	-0.011	0.714	0.007	0.008
		(0.121)	(0.012)	(0.013)	(0.005)	(0.003)	(0.01)	(0.503)	(0.013)	(0.007)
Female	615,040	0.172	0.018	0.017	0.008	0.013	-0.002	0.491	0.018	0.016
		(0.152)	(0.017)	(0.016)	(0.014)	(0.008)	(0.004)	(0.633)	(0.019)	(0.022)
Lower education	527,816	0.041	0.009	0.007	0.001	0.007	0.005	0.327	0.014	0.019
		(0.109)	(0.013)	(0.013)	(0.01)	(0.007)	(0.006)	(0.468)	(0.019)	(0.018)
Higher education	647,272	0.227	0.024*	0.019	0.002	0.006	-0.013	0.689	0.007	0.002
		(0.138)	(0.014)	(0.014)	(0.008)	(0.005)	(0.008)	(0.582)	(0.014)	(0.012)
Non-employee	839,030	0.118	0.012	0.008	0.001	0.007	-0.003	0.436	0.008	0.015
		(0.141)	(0.017)	(0.014)	(0.008)	(0.005)	(0.006)	(0.496)	(0.015)	(0.018)
Employee	336,058	0.279**	0.03***	0.032**	0.008	0.008	-0.014	0.954	0.021	0.005
		(0.122)	(0.009)	(0.016)	(0.011)	(0.006)	(0.009)	(0.599)	(0.017)	(0.011)
Age group										
19-29	275,322	0.296**	0.03**	0.028*	0.01	0.007*	-0.017*	0.751	0.017	0.014*
		(0.14)	(0.015)	(0.015)	(0.011)	(0.004)	(0.01)	(0.502)	(0.011)	(0.008)
30-39	307,338	0.188	0.02	0.017	-0.002	0.006	-0.009	0.44	0.007	0.006
		(0.177)	(0.015)	(0.019)	(0.01)	(0.008)	(0.007)	(0.538)	(0.018)	(0.014)
40-49	295,190	0.24	0.016	0.015	0.008	0.015*	-0.01	0.961	0.021	0.015
		(0.217)	(0.023)	(0.024)	(0.015)	(0.008)	(0.008)	(0.708)	(0.022)	(0.023)
50-59	216,426	0.201	0.039**	0.029**	0.013	0.013	0.005	0.619	0.024	0.025
		(0.131)	(0.016)	(0.012)	(0.012)	(0.01)	(0.007)	(0.688)	(0.027)	(0.025)
60-65	80,812	-0.29*	-0.029**	-0.028	-0.032	-0.018*	0.005	0.01	-0.008	-0.004
		(0.171)	(0.013)	(0.018)	(0.02)	(0.011)	(0.011)	(0.448)	(0.014)	(0.012)

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2013 and 2018 data. Overweight and obesity indicators were estimated using Asian and WHO cutoff. Estimated using doubly robust difference-in-differences method. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, median working age, access to clean toilet and water, access to health insurance, health care availability, # of establishments, and male-female ratio.

Table A3 Impact pathways of super apps effects: Physical activity vs. unhealthy food consumption

Impact pathways using Riskesdas	*Σ districts*	*Mean*	*Coefficient*
Time doing hysical activity in the past week			
Log(Heavy activity time)	994	6.57	0.055
			(0.122)
Log(Moderate activity time)	994	6.54	0.002
			(0.098)
Doing heavy activity (min. 60 minutes)	994	0.99	0.003
			(0.003)
Doing moderate activity (min. 150 minutes)	994	0.93	-0.007
			(0.014)
Ever consume the following food in past week			
Sweet food/drinks	994	0.95	0.006
			(0.005)
Salty food	994	0.89	0.035*
			(0.018)
Fatty/fried food	994	0.96	0.004
			(0.005)
Grilled food	994	0.87	0.009
			(0.018)
Dried food	994	0.68	0.021
			(0.041)
Artificial flavoring	994	0.91	-0.016
			(0.014)
Caffeinated drinks	994	0.34	0.016
			(0.026)
Noodles/instant food	994	0.94	0.004
			(0.009)

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2013 and 2018 data. Estimated using doubly robust difference-in-differences method. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, median working age, access to clean toilet and water, access to health insurance, health care availability, # of establishments, and male-female ratio.

Table A4 The effects of super apps on weekly food group expenditure (in real Rupiah)

Variable name	***Mean***	***Coefficient***
Expenditure of rice	52,614	1.447
		(2,068.028)
Expenditure of fish	28,685	1,125.984
		(1,091.192)
Expenditure of meat	42,708	4,479.168***
		(1,396.485)
Expenditure of legumes	10,029	634.111
		(396.032)
Expenditure of vegetable	27,808	575.151
		(786.776)
Expenditure of fruit	19,717	3,821.395***
		(953.604)
Expenditure of sugar	12,583	-746.925
		(583.708)
Expenditure of oil	10,912	-211.364
		(298.155)
Expenditure of prepared food	132,550	12,434.68***
		(4,035.032)
Expenditure of cigarette	47,447	769.366
		(1,214.586)
Total observations		994

Note: *** p<0.01, ** p<0.05, * p<0.10. ‡ calculated for per capita in households. Estimations are calculated using doubly robust difference-in-differences methods. Variables are aggregated at the district level from Susenas 2012 and 2019 data. Covariates to ensure conditional parallel trend are the following: internet access, regional gas price, GDP per capita, employment, urban residence, median working age. 1 US$ = Rp 14,196