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The nutrition transition in low- and middle-income countries: The role of socioeconomic factors, culture, and the food environment

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Abstract

Many low- and middle-income countries (LMICs) are undergoing a nutrition transition, where diets are shifting from traditional staples to energy-dense processed foods, often contributing to poor nutrition outcomes, including overweight and obesity. In a fast-changing world, understanding the contributing factors and pockets of vulnerability enables better targeting in a resource-constrained context with competing development priorities. This dissertation contributes to this policy discussion by examining overlooked and novel drivers of the nutrition transition in LMICs and identifying when and where prevention can yield the greatest health gains. Using longitudinal and large-scale survey data from Indonesia and various econometric modeling approaches, this dissertation links nutritional outcomes with crisis exposure, cultural practices, and the expansion of digital platforms to uncover both risks of malnutrition and poor health and potential mitigation strategies.

The first essay shows that early-life exposure to crisis imposes lasting health costs. Children under five in households that faced high rice prices and economic hardships during the Asian financial crisis in the late-1990s were more likely to suffer from stunting and, as adults, remained shorter with a higher body mass index (BMI). These patterns likely contribute to Indonesia's rising overweight and obesity rates. This essay also demonstrates the heterogeneous impacts of crises across population groups. Macroeconomic shocks often hit urban populations harder than rural ones, boys more than girls, and children with lower-educated mothers more than those with mothers who have higher education levels. These findings highlight the need for tailored crisis mitigation strategies and for leveraging protective factors in intervention efforts.

The second essay examines household dynamics that contribute to gendered differences in nutritional investments. Patriarchal norms, especially patrilocality, are linked to lower female BMI, with the largest negative effects among underweight women. In contrast, matrilocality and bridewealth practices appear protective for women's well-being. The positive association between certain customs and BMI is strongest for those already overweight, while patrilocality's adverse effects are concentrated among the underweight, underscoring a polarizing influence of culture on nutrition. These findings shed light on the invisible dynamics that can hamper effective intervention and highlight the need to explicitly integrate cultural practices into the policy sphere.

The third essay moves the discussion from the household level to the environment level. This study assesses the impact of modern food environments on the nutrition transition by exploiting the staggered rollout of Indonesian "super apps" (mobile applications providing food delivery, ride-hailing, e-commerce) in 2015-2018. This study shows that exposure to super apps increases BMI and the risk of being overweight or obese. This finding can be explained by an increase in the consumption of unhealthy and processed foods. At the same time, these super apps and online platforms have the potential to reduce undernutrition and improve dietary diversity. These findings indicate the double-edged roles of modern food environments and the need to mitigate their negative effects through improved regulations and policies.

Together, this dissertation contributes to a better understanding of drivers of the nutrition transition in LMICs, offering important evidence in identifying critical windows and settings for intervention: crisis-responsive policies, gender-sensitive strategies, and balanced governance of digital food platforms.

Der Ernährungswandel in Ländern mit niedrigem und mittlerem Einkommen: Die Rolle sozioökonomischer Faktoren, kultureller Praktiken und des Lebensmittelumfelds

Zusammenfassung

Viele Länder mit niedrigem und mittlerem Einkommen (LMIC) durchlaufen einen Ernährungswandel, bei denen sich die Ernährung von traditionellen Grundnahrungsmitteln zu energiereichen verarbeiteten Lebensmitteln verlagert, mit nachteiligen Folgen für Ernährung und Gesundheit. In einer sich rasch verändernden Welt ermöglicht das Verständnis zentraler Bestimmungsfaktoren und Vulnerabilitäten eine gezieltere Ausrichtung von Maßnahmen in ressourcenbeschränkten Kontexten mit konkurrierenden Entwicklungsprioritäten. Diese Dissertation trägt zu dieser politikorientierten Debatte bei, indem sie bisher übersehene sowie neue Treiber des Ernährungswandels in LMIC untersucht und identifiziert, wann und wo Prävention die größten Gesundheitsgewinne erzielen kann. Anhand von Längsschnitt- und großangelegten Umfragedaten aus Indonesien und mithilfe ökonometrischer Modelle verknüpft die Arbeit Ernährungsergebnisse mit Krisenexposition, kulturellen Praktiken und der Ausweitung digitaler Plattformen, um sowohl Risiken als auch Ansatzpunkte für deren Minderung offenzulegen.

Der erste Aufsatz zeigt, dass Krisenexposition im frühen Kindesalter dauerhafte Gesundheitskosten verursacht. Kinder unter fünf Jahren in Haushalten, die während der asiatischen Finanzkrise Ende der 1990er Jahre mit hohen Reispreisen und wirtschaftlichen Schwierigkeiten zu kämpfen hatten, waren häufiger von Wachstumsstörungen betroffen und blieben als Erwachsene kleiner und hatten einen höheren Body-Mass-Index (BMI). Diese Muster dürften zu den steigenden Übergewichts- und Adipositasraten in Indonesien beitragen. Der Aufsatz dokumentiert zudem heterogene Wirkungen über Bevölkerungsgruppen hinweg: Makroökonomische Schocks treffen die städtische stärker als die ländliche Bevölkerung, Jungen stärker als Mädchen, und Kinder von Müttern mit niedrigerer Bildung stärker als jene mit höher gebildeten Müttern. Die Befunde unterstreichen den Bedarf an maßgeschneiderten Strategien zur Krisenbewältigung sowie an der Stärkung protektiver Faktoren in Interventionen.

Der zweite Aufsatz untersucht haushaltsinterne Dynamiken, die zu geschlechtsspezifischen Unterschieden in Ernährungsinvestitionen beitragen. Patriarchale Normen, insbesondere Patrilokalität, stehen mit einem niedrigeren weiblichen BMI in Zusammenhang; die stärksten negativen Effekte zeigen sich bei untergewichtigen Frauen. Matrilokalität und Brautpreispraktiken erscheinen demgegenüber protektiv für das Wohlbefinden von Frauen. Der positive Zusammenhang bestimmter Bräuche mit dem BMI ist bei bereits übergewichtigen Personen am ausgeprägtesten, während die nachteiligen Effekte der Patrilokalität sich auf Untergewichtige konzentrieren, ein Hinweis auf den polarisierenden Einfluss kultureller Praktiken auf Ernährung. Diese Ergebnisse legen verborgene Dynamiken offen, die wirksame Interventionen behindern können, und zeigen die Notwendigkeit, kulturelle Praktiken explizit in die Politikgestaltung zu integrieren.

Der dritte Aufsatz verlagert die Perspektive von der Haushaltsebene auf die Umweltebene. Die Studie bewertet die Auswirkungen moderner Lebensmittelumgebungen auf den Ernährungswandel, indem sie die gestaffelte Einführung indonesischer „Super-Apps“ (für Lebensmittellieferungen, Ride-Hailing und E-Commerce) in den Jahren 2015–2018 ausnutzt. Sie zeigt, dass die Exposition gegenüber Super-Apps den BMI sowie das Risiko für Übergewicht und Adipositas erhöht, was sich durch einen höheren Konsum ungesunder und (hoch-)verarbeiteter Lebensmittel erklären lässt. Zugleich bergen diese Super-Apps und Online-Plattformen Potenziale zur Verbesserung von Unterernährung und Ernährungsvielfalt. Insgesamt weisen die Befunde auf die zweischneidige Rolle moderner Lebensmittelumgebungen hin und verdeutlichen den Bedarf, negative Effekte durch eine ausgewogene Regulierung und geeignete Politikinstrumente zu begrenzen.

In der Summe vertieft die Dissertation das Verständnis der Triebkräfte des Ernährungswandels in LMIC und liefert Evidenz zur Identifikation kritischer Zeitfenster und Kontexte für Interventionen: krisenreaktive Politiken, geschlechtersensible Strategien sowie eine ausgewogene Regulierung digitaler Lebensmittelplattformen.

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List of abbreviations

BCC	:	Behavioral change communication
BMI	:	Body mass index
BMIZ	:	Body mass index-for-age z-scores
BPS	:	Badan Pusat Statistik
CI	:	Confidence intervals
CPI	:	Consumer price index
CRE	:	Correlated random effects
DBM	:	Double Burden of Malnutrition
DiD	:	Difference-in-Differences
FE	:	Fixed effects
GDP	:	Gross domestic product
HAZ	:	Height-for-age z-scores
HH	:	Household
IFLS	:	Indonesian Family Life Survey
IPW	:	Inverse probability weight
LMIC	:	Low- and middle-income countries
Podes	:	Village Potential Census (*Potensi Desa*)
RE	:	Random effects
RIF	:	Recentered influence function
Riskesdas	:	Basic Health Survey (*Riset Kesehatan Dasar*)
Susenas	:	National Socioeconomic Survey (*Survei Sosioekonomi Nasional*)
UQR	:	Unconditional quantile regressions
WAZ	:	Weight-for-age z-scores
WHO	:	World Health Organization

List of publications

Parts of this dissertation have been published in peer-reviewed journals:

1) Elmira, E. S., & Qaim, M. (2025). Macroeconomic shocks and long-term nutritional outcomes: Insights from the Asian financial crisis. *Global Food Security*, 100900. https://doi.org/10.1016/j.gfs.2025.100900
The published version is reproduced in Chapter 2 of the thesis.

2) Elmira, E. S., Chichaibelu, B. B., & Qaim, M. (2024). Marriage customs and nutritional status of men and women. *Food Policy*, *128*, 102734. https://doi.org/10.1016/j.foodpol.2024.102734
The published version is reproduced in Chapter 3 of the thesis.

3) Elmira, E. S., & Suryahadi, A. (2025). The impact of super apps on the nutrition transition in low- and middle-income countries: Evidence from Indonesia. *Economics and Human Biology*, 59, 101524. https://doi.org/10.1016/j.ehb.2025.101524
The published version is reproduced in Chapter 4 of the thesis.

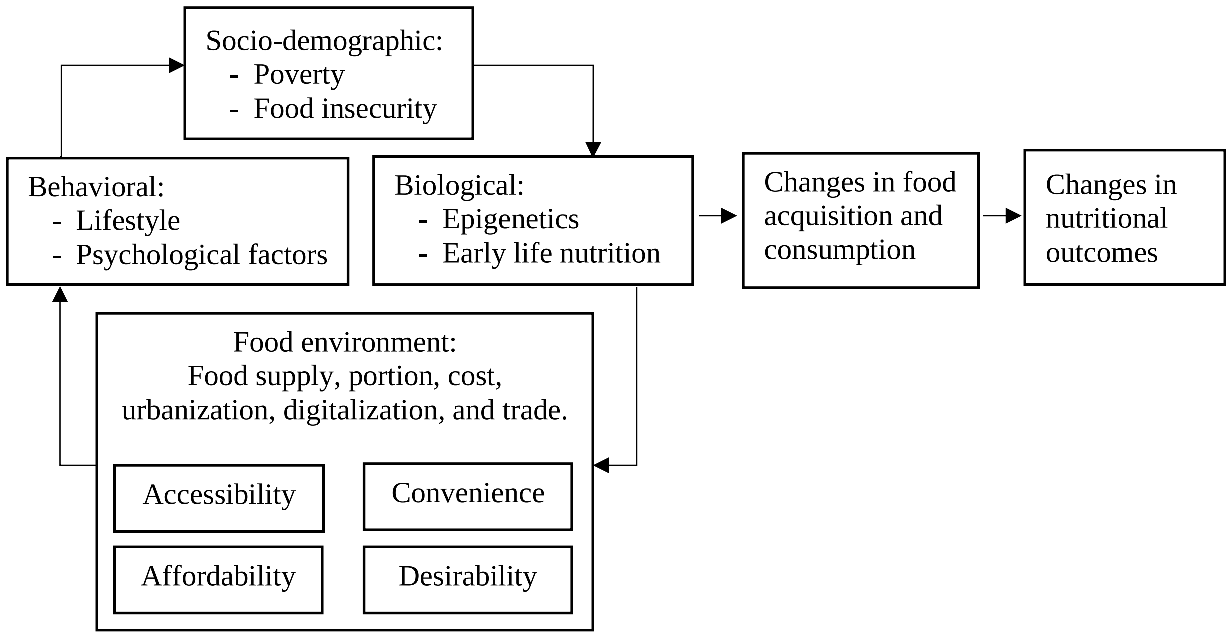
1 Introduction and motivation

1.1 Problem statement and conceptual framework

The nutrition transition, defined as the shift from traditional staple diets to energy-dense processed foods and reduced physical activity, often contributes to poor nutritional outcomes worldwide (Brouwer et al., 2021, Popkin & Ng, 2022). Around 2.5 billion adults are overweight or obese, increasing their risk of cardiovascular diseases, diabetes, and cancer (Brauer et al., 2024, Ford et al., 2017, Okunogbe et al., 2021). At the same time, many low- and middle-income countries (LMICs) are still facing stagnation in the elimination of undernutrition, despite a global decline in stunting rates. This coexistence of undernutrition (e.g., underweight, stunting, wasting) and overweight, obesity, or diet-related illnesses is defined as the double burden of malnutrition (DBM) (Popkin et al., 2020). Countries with rapid nutrition transition, such as Indonesia, India, and those located in sub-Saharan Africa, are reported to have severe cases of DBM. The health cost of DBM is significant, which will further hinder economic development in LMICs (Bhutta et al., 2023, Okunogbe et al., 2021). While the nutrition transition in LMICs has now received much attention, some aspects remain poorly explained. These gaps risk undermining efforts to alleviate malnutrition (Ford et al., 2017).

Malnutrition is a byproduct of complex interactions of biological, socio-demographic, environmental, and behavioral vulnerabilities (World Health Organization, 2016). Socio-demographic factors, such as poverty and food insecurity, influence biology through epigenetics and early-life nutrition, leaving individuals susceptible to long-term poor health outcomes (See Figure 1.1). Broader environmental exposures, such as logistics, marketing, urbanization, digitalization, and trade, can shift consumption patterns by making certain types of food (e.g., ultra-processed, unhealthy) more accessible, affordable, convenient, and desirable (Turner et al., 2018). Lastly, behavioral factors, including lifestyle, psychological factors, and preferences, may influence an individual's decision in food consumption. The interaction of these factors can create a feedback loop, whereby malnutrition in one generation can lead to biological and socio-demographic vulnerabilities in the next, perpetuating cycles of poor nutrition and health. This dissertation aims to address critical research gaps on the determinants of the nutrition transition in the context of LMICs and to actively inform policy discussions aimed at preventing malnutrition.

Figure 1.1 Determinants of malnutrition



Note: Graphic re-illustrated from determinants of malnutrition (World Health Organization, 2016).

Previous studies show that obesity and metabolic diseases have developmental origins. Specifically, poor nutrition during pregnancy or early infancy, often due to poverty or food insecurity, increases future risk for non-communicable diseases (Knop et al., 2018, Markopoulou et al., 2019, van Dijk et al., 2015). Building on this theory, long-term research on the Great Chinese Famine finds that in utero or early infancy exposure to famine leads to lasting effects on height, physical and cognitive abilities, and non-communicable diseases (Cui et al., 2020, Gørgens et al., 2012, Kim et al., 2017, Mu & Zhang, 2011, Yu et al., 2018). One possible explanation for these findings is that famine or other similar crises can cause short-term malnutrition that can extend into adulthood, such as wasting or stunting (Akresh et al., 2011, Woldemichael et al., 2022, Yamauchi & Larson, 2019). Importantly, such childhood malnutrition can in turn increase the risk of overweight and obesity in adulthood, further exacerbating the risk for other metabolic diseases (Cui et al., 2020, Gørgens et al., 2012, Zheng et al., 2012).

Recent global crises have severe implications for nutrition (Hawkes et al., 2022, Headey et al., 2020, Osendarp et al., 2021, Saccone, 2021). Disadvantaged individuals in LMICs are among those at a greater risk of long-term adverse health events due to these crises. Severe crises, such as famines, regional conflict, or crop failures, clearly contribute to malnutrition (Akresh et al., 2011, Akresh et al., 2012, Woldemichael et al., 2022, Yamauchi & Larson, 2019). Less severe crises, such as macroeconomic, financial, or political crises, are reported to have a mixed effect on nutrition (Block et al., 2004, Frankenberg et al., 1999, Strauss et al., 2004, Yamauchi & Larson, 2019). This ambiguity may be driven by confounding factors such as crisis type, severity, location, mitigation strategies, and gender (Akresh et al., 2011, Block et al., 2004, Gørgens et al., 2012, Mu & Zhang, 2011, Webb, 2010, Yamauchi & Larson, 2019). Understanding the impact of different types of crises and their modifying factors on nutrition is crucial for developing target-specific mitigation strategies.

Beyond socioeconomic factors, cultural practices can play a more substantial role in determining within-household malnutrition in some contexts (Gaupholm et al., 2023). Specifically, broader cultural norms, networks, and preferences for traditional diets can influence food choice and dietary quality (Brown, 1991, Klaczynski et al., 2004, O'Dea, 2008). These practices may also contribute to gender disparity of overweight and obesity (Popkin et al., 2020, Roemling & Qaim, 2012, Roemling & Qaim, 2013). Cultural practices that limit women's mobility, impose weak bargaining power, and reflect a preference for sons may reduce households' investment in women's nutrition (Ameye & Swinnen, 2019, Hansford, 2010, Rathore & Das, 2022, Wells et al., 2012). However, the role of other cultural norms, such as marriage customs, are less clear, as the evidence on this topic is rather mixed (Allendorf, 2013, Briones et al., 2018, Levine & Kevane, 2003, Lowes, 2020, Lowes & Nunn, 2017, Ren et al., 2014, Sear & Mace, 2008). In summary, these findings suggest that the effects of cultural practices on nutrition may be context-dependent and require further investigation.

Another challenge in eliminating malnutrition in LMICs is the rapid changes in the food environment, which can exacerbate the nutrition transition. The food environment refers to the interactions between people and the broader food system, where individuals obtain and consume food (Turner et al., 2018). Improved welfare and economic activities, including global trade, urbanization, media, marketing, and technological adaptation, have contributed to changes in the food environment (Ng & Popkin, 2012, Popkin & Ng, 2022). These factors make unhealthy and ultra-processed food options more accessible, affordable, convenient, and desirable. These changes may accelerate an intergenerational shift in diet and nutrition, leading to a concerning increase in overweight and obesity (World Health Organization, 2016).

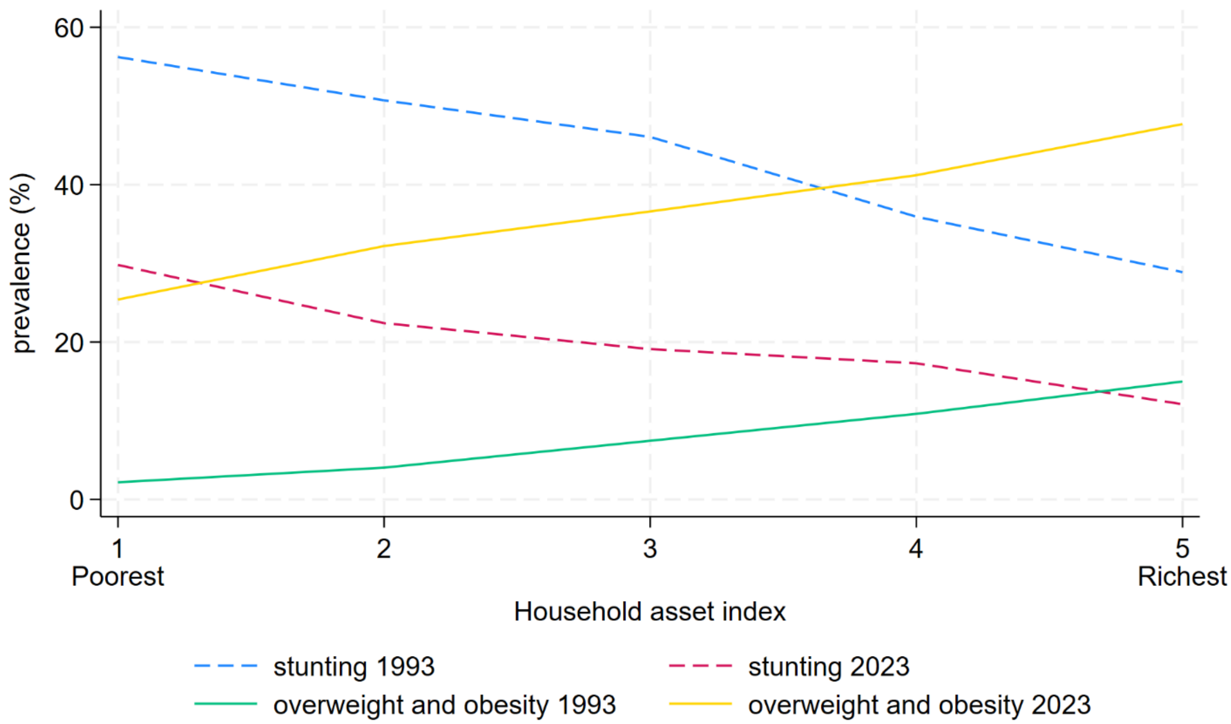
Modern food environment components, such as digital platforms, modern marketing, and out-of-home food, remain understudied in the LMIC context (Andreyeva et al., 2011, Granheim et al., 2022). A clear example is the expansion of on-demand companies in LMICs, which create a single app for various services, including online food order and delivery, ride-hailing, and e-commerce, also known as super apps (Azzuhri et al., 2018). Although these apps aim to improve convenience and access to goods, they may have inadvertently encouraged unhealthy lifestyles by reducing physical activity or increasing consumption of energy-dense and ultra-processed foods (Horta et al., 2022, Maimaiti et al., 2018). Given the massive expansion of such services in LMICs, understanding their impact on health outcomes becomes essential. This understanding may allow us to leverage their strengths to improve health outcomes rather than worsen them.

1.2 Research area context

This dissertation examines Indonesia as a case study of the nutrition transition in LMICs. As a growing middle-income country, Indonesia has undergone a major economic transformation since the early 2000s and now faces challenges in its nutrition transition (De Pee et al., 2021). Indonesia's gross domestic product (GDP) has grown significantly due to the commodity boom in 2003, and the country managed to graduate as an upper- and middle-income country in 2019 (World Bank, 2023). On the other hand, during the same period, Indonesia managed to attain the title for the world's largest case of a severe double burden of malnutrition (Popkin et al., 2020, Roemling & Qaim, 2012). This is further shown by the exponential increase in overweight and obesity incidences in Indonesia since 1993, which continues to rise at twice the global rate (Rachmi et al., 2017). At the same time, stunting rates among children have persisted at around 25 %–30 %, which undermines economic development and compromises future health (Badan Penelitian dan Pengembangan Kesehatan, 2019).

The nutrition transition trajectory in Indonesia varies across population groups. For example, the female population suffers 1.8 times higher overweight and obesity incidences than men, suggesting gender disparity in health (World Health Organization, 2021). In addition, malnutrition affects people across socioeconomic levels, indicating the need to investigate factors beyond welfare. To illustrate these trends, Figure 1.2 shows the prevalence and trajectory of malnutrition across periods and welfare levels in Indonesia, measured by stunting and overweight/obesity. The incidence of overweight/obesity increased from 1993 to 2023, while stunting rates, although declining, remained high. Specifically, in 2023, among individuals in the lowest asset quintile, approximately 25% were overweight or obese, and 30% were stunted. In contrast, among those in the top quintile, approximately 48% were overweight or obese, and 12% were stunted (See Figure 1.2).

Figure 1.2 Prevalence of stunting and overweight/obesity across household welfare levels in 1993 and 2023.



Note: Calculations for 1993 are based on the Indonesian Family Life Survey (IFLS) 1993; stunting 2023 prevalence is obtained from Ministry of Health report in 2024 (Kemenkes, 2024), and adult overweight/obesity 2023 prevalence is obtained from Ministry of Health report in 2023 (Kemenkes BKPK, 2023). Stunting is measured for children under five years, and overweight/obesity for adults aged 19 and above. The household asset index was calculated using principal component analysis, following the methods explained in the Kemenkes 2023-2024 report, based on the following variables: household ownership, electricity access, toilet types, housing characteristics (wall, floor, and roof), and asset ownership (vehicles, livestock, appliances, and jewelry).

Limited nutrition policy interventions coupled with the rapid nutrition transition in Indonesia weaken efforts to alleviate malnutrition. Policies related to the prevention of overweight and obesity are often poorly executed and lack enforcing regulations or enabling environments such as fiscal support, directive orders, or legal frameworks (UNICEF, 2022). The stunting alleviation programs were hindered by the significant regional variation in malnutrition, high poverty rates, limited access to diverse and high-quality diets, and poor multisectoral coordination (Sardjunani & Achadi, 2016). Issues of food safety and institutional weaknesses now plague the recent controversial large-scale meal program aimed at improving food security among schoolchildren[1]. The massive expansion of packaged food retail and online food delivery services has also significantly influenced dietary patterns towards energy-dense and ultra-processed foods (Hawkes, 2005, Safira & Chikaraishi, 2022). These situations indicate the lack of commitment and implementation of nutrition-related policies in Indonesia. Understanding what factors contribute to the nutrition transition in Indonesia and identifying the most vulnerable populations affected by these shifts are pertinent in driving targeted and effective nutrition policy reform.

1.3 Research questions and objectives

While previous research has investigated different aspects of malnutrition determinants, there are still some gaps in understanding the roles of socioeconomic factors, culture, and the food environment. To address these knowledge gaps, this dissertation focuses on three main research questions:

- What is the impact of macroeconomic crisis on the immediate and long-term nutritional outcomes?
  This essay aims to estimate the impact of childhood exposure to macroeconomic crisis on immediate and long-term nutritional outcomes, focusing on heterogeneous effects based on gender, regions, and socioeconomic groups.
- How do cultural practices affect the gendered differences in nutritional outcomes?
  This essay aims to estimate the impact of cultural practices such as co-residence after marriage and bridewealth on the nutritional outcomes of males and females.
- What is the impact of the expansion of super apps providing online food order and delivery services on nutrition outcomes and food consumption patterns in LMICs?
  This essay aims to estimate the impact of exposure to the expansion of super apps on adult nutritional outcomes and food consumption patterns, focusing on heterogeneous effects by gender, region, and socioeconomic group.

[1] https://www.lowyinstitute.org/the-interpreter/indonesia-s-free-meal-ambition-when-policy-becomes-recipe-risk

1.4 Methodology

1.4.1 Data

This dissertation uses available secondary health and socioeconomic datasets to answer the three research questions (See Table 1.1). The first research question was answered using data available from the Indonesian Family Life Survey (IFLS). The second research question combines IFLS and Ethnographic Atlas data. The third research question combines digital platform expansion data with Riskesdas, Susenas, and Podes datasets.

IFLS is a longitudinal household survey conducted by the RAND Research Institute covering 13 provinces in Indonesia (Strauss et al., 2016). The survey is representative of 83 % of the Indonesian population, with a total attrition rate of 13 % due to migration and death. This survey followed an initial sample of 7,224 households in 1993, which were subsequently re-surveyed in 1997, 2000, 2007, and 2014. IFLS gathered comprehensive data on anthropometric outcomes, household and individual characteristics, and community information.

The primary objective of this dissertation is not to assess the current nutritional situation in Indonesia, but to understand the underlying mechanisms driving its nutrition transition. While IFLS data reflects household conditions from earlier periods, it contains unique information not available in more recent surveys (i.e., Riskesdas, the Demographic Health Survey), which makes it possible to explore these mechanisms. For example, IFLS collects detailed information on ethnicity, community practices, and local rice prices, which can be used to examine the role of socioeconomic changes and cultural factors in the nutrition transition. Additionally, IFLS collected information over a 21-year span and tracked an individual's anthropometric status across different life stages, allowing for a long-term analysis. It also features a panel structure that allows for more robust econometric approaches.

Food and non-food inflation data are collected monthly by the World Bank at the national level to construct the consumer price index (CPI). Only inflation data collected between 1997 and 2000 were used in this study to depict the price spike during the Asian Financial Crisis in the late 1990s. The source of the inflation information is an official release by the Indonesian Statistics Agency (*Badan Pusat Statistik* – BPS).

The Ethnographic Atlas compiles data on the ethnographic observations of traditional cultural practices of 1,291 ethnic groups worldwide (Murdock, 1967). This dataset contains information on marriage customs, inheritance customs, sex and age differences in agricultural and other occupational practices, as well as other relevant traditional practices. There are 13 ethnicities from this atlas that can be merged with the ethnicities in IFLS. Twelve ethnicities have roots in the Insular Pacific region, and one ethnic (Malays) has East Eurasian roots.

The Basic Health Survey (Riskesdas) is a repeated cross-sectional health survey conducted every 3-4 years, collecting information on nutritional status, unhealthy food consumption, and physical activity from over 300,000 households across 497 districts in Indonesia. It does not have a panel structure. Incorporating the population weight, the 2007, 2013, and 2018 datasets are representative at the district level in Indonesia, while the 2010 dataset is only representative at the province level. This survey not only collects information but also blood specimen sampling for testing of blood glucose, hemoglobin, and other clinical chemistry indicators.

The National Socioeconomic Survey (Susenas) is a repeated cross-sectional survey conducted annually by BPS, providing information on household and individual sociodemographic characteristics, welfare information, and detailed food consumption from approximately 300,000 households. Susenas does not have a panel structure. The consumption modules collect information on food and non-food expenditures, as well as macronutrient intake, for each food item and food group. Susenas' estimation variables are representative up to the district level.

Village Potential (Podes) is a village-level census conducted every 3-4 years that collects data on available infrastructure, socioeconomic conditions, and resources. The survey is conducted by BPS by collecting information through the village office.

Digital platform expansion data contains the launch date information for each district served by the two largest digital super app platforms in Indonesia, Gojek and Grab. Both companies began their operations in Indonesia in 2015 and have implemented a staggered rollout of their services across districts in Indonesia. Gojek officially provided the launch date information for each district where they operate. For Grab, this information was gathered by tracking the news in local media outlets or social media.

Table 1.1 Dataset list and characteristics

Data name	**Data type**	**Sample size**	**Modules**	**Relevant variables**
Indonesian Family Life Survey (IFLS)	Panel data collected in 1993, 1997, 2000, 2007, and 2014.	7,330 households in Indonesia.	Household (HH) characteristics and economy, adult, under 15 children, ever-married women, anthropometric measures, and community infrastructure, livelihood, and customs.	Weight, height, HH characteristics, individual sociodemographic, economic hardships, ethnicity, community culture and marriage customs, community rice price.
Inflation data	Cross sectional	497 districts	N/A	Food, non-food, and general inflation
Ethnographic Atlas	Cross sectional data collected in 1967	1,297 ethnicities worldwide	Marriage customs, inheritance law, kinship, sex and age differences in occupation, dwelling types, linguistics	Co-residence after marriage, bridewealth
Basic Health Survey (*Riset Kesehatan Dasar* - Riskesdas)	Repeated cross sectional	±300,000 households	Non-communicable diseases, communicable diseases, HH hygiene and welfare, anthropometric measurements, health knowledge, reproduction and child health	Anthropometric measurements, HH and individual characteristics, physical activity, unhealthy food frequency
National Socioeconomic Survey (*Survei Sosioekonomi Nasional* - Susenas)	Repeated cross sectional	±300,000 households	Demographic, labor, usage of technology and communication, social protection program, food items and groups consumption	HH food expenditure, food quantity, and macronutrient intake, HH and individual characteristics
Village Potential Census (*Potensi Desa* - Podes)	Repeated village census	77,961 villages	Livelihood, geographical information, infrastructure, socioeconomic network	Education and health infrastructures
Digital platforms expansion data (Gojek and Grab)	Cross sectional from 2015	497 districts	N/A	Application official launch dates information

1.4.2 Indicators and variables

The main outcome observed in this dissertation was the changes associated with the nutrition transition in Indonesia. The nutrition transition can be measured using several indicators, which are described below:

- Body mass index (BMI)

  This indicator is measured by dividing weight in kilograms by height in meters. The result is a score that can be categorized into different nutritional statuses.
- Adult nutritional status

  Using the BMI score, we can categorize individuals into different nutritional statuses (i.e., overweight, obese, underweight). This dissertation uses two different cutoffs: the World Health Organization (WHO) and the Asian population. The WHO cutoff provides categorization that is comparable worldwide. The Asian population cutoff provides a more relevant categorization in the sample population, whereby it determines overweight and obesity at a lower cutoff (Tan, 2004).
- Growth z-scores

  These indicators are used to monitor a child's growth and nutritional status. It calculates how far the observed weight, height, weight-to-height ratio, and BMI of a child deviate from those of other children of the same age and sex in the reference population. The resulting score is expressed in standard deviation units, which can be categorized into different nutritional statuses.
- Children's nutritional status

  Using the growth z-scores, the nutritional status of children can be categorized into different classifications such as stunting, wasting, underweight, overweight, and obese.
- Food consumption

  Per capita food items and food groups consumption is calculated by dividing the indicators by the number of household members. Food items are grouped based on major categories, including a separate group for prepared food (i.e., rice/noodle dishes, prepared meat, snacks) to measure unhealthy food consumption.

- Physical activity

  This indicator measures the number of minutes individuals engaged in rigorous (i.e., lifting heavy objects, participating in sports) and moderate (i.e., cooking, walking) physical activity in the past week.

The exposure for each empirical essay differs. Essay 1 measures crisis exposure using two indicators: community rice price inflation and reported household economic hardship during the Asian Financial Crisis in 1998/1999. Community rice price was constructed as both nominal and real prices (adjusted by the CPI) and calculated on a monthly basis throughout 1997-2000. This price data is then matched with the household's original community at baseline to construct a variable indicating exposure to macroeconomic crisis. Essay 2 examines cultural practices exposure by leveraging on ethnic-based marriage customs such as co-residence with paternal parents (patrilocality), co-residence with maternal parents (matrilocality), and bridewealth. Here, an individual's ethnicity in the IFLS data is linked with corresponding ethnographic information from the Ethnographic Atlas to obtain the ethnicity-based marriage customs. Essay 3 identifies exposure to digital platforms by using the staggered rollout of the two largest super apps in Indonesia beginning in 2015.

1.4.3 Methods

Each essay employs advanced econometric approaches to examine the causal relationships between macroeconomic crises, marriage customs, and digital food environments, and their impact on the nutrition transition in Indonesia (See Table 1.2). Essay 1 exploits the regional variation of staple food price inflation and estimates its effect on nutritional outcomes using panel data analysis with individual and year fixed effects. This approach ensures that the treatment indicator is exogenously determined by the crisis rather than by household mitigation strategies or other confounding factors. For the second essay, a fixed-effect estimator is not feasible due to the static nature of ethnicity-based information. Therefore, a correlated random effects (CRE) estimator is used as this approach controls for time-invariant unobserved heterogeneity without requiring explanatory variables to be time-variant. Essay 3 leverages the staggered rollout of two major digital platforms from 2015 until 2018 in Indonesia. A difference-in-differences (DiD) approach is used to compare nutritional outcomes between the treatment and control groups before and after super apps adoption. A doubly robust estimator is used by combining inverse probability weighting (IPW) and outcome regression, ensuring balanced characteristics between the treatment and control groups.

While the three essays employ rigorous causal inference strategies, achieving perfect causal identification with observational data is challenging and some sources of endogeneity may still remain. These limitations and how they were addressed are discussed in the next section.

Table 1.2 Data analysis methods

Research question	**Method**
What is the impact of macroeconomic crisis on the immediate and long-term nutritional outcomes?	Panel data analysis with individual and year fixed effects and plausibly exogenous regional variation of rice price inflation
How do cultural practices affect the gendered differences in nutritional outcomes?	Pooled cross-sectional data analysis using the correlated random effects (CRE) estimator
What is the impact of the expansion of super apps providing online food order and delivery services on nutrition outcomes and food consumption patterns in LMICs?	District-aggregated and individual DiD with a doubly-robust estimator (inverse probability weight and outcome regression)

1.5 Limitations

The main limitation in Essay 1 is associated with the measurement of the community rice price in 2000. A small number of communities reported no significant increase in rice prices and even a decrease in prices during the crisis period, indicating a post-crisis recovery. This means that the rice prices in the data may not fully capture the intensity of the crisis, potentially leading to an underestimation of the results. To corroborate the rice price estimation, an additional analysis was conducted using household reports of economic hardship during the crisis period, showing consistent results.

The limitation in Essay 2 is related to how ethnicity-based marriage customs may not reflect actual marital practices. To test this assumption, additional regressions were performed to assess the effect of the actual practices of co-residence with paternal and maternal parents after marriage and the payment of bridewealth in a small subset of samples. The estimated effects remain consistent in magnitude and direction, reflecting alignment in ethnic customs and actual practices. Additionally, while the correlated random effect (CRE) estimator controls for time-invariant unobserved heterogeneity, it is possible that ethnic-based marriage customs still capture broader socioeconomic, cultural factors, and inherent child-rearing differences beyond marriage customs. As a result, the observed results in this essay must be interpreted as an association and not as causal effects of marriage customs on nutritional outcomes.

One important limitation of Essay 3 is that the entry of digital platforms into the district is likely not random and may be determined by factors beyond what the available data can capture. While the conditional parallel trend is captured in the estimation, it is possible that factors such as political support for digital infrastructure, market demand trends, and other macro-level indicators also play a role in determining entry and may affect the trend in nutritional outcomes. However, the baseline covariates used in this essay already explain approximately 65 % of the variation in platform entry decisions, thereby reducing bias from selection into treatment.

1.6 Organization of the dissertation

This dissertation is organized into five chapters. Chapter 1 (this current chapter) lays out the background, motivation, and research area context. This chapter also provides a brief explanation of the data and methodology used to write each empirical essay. Chapter 2 contains the first essay examining how early-life exposure to the 1998/1999 macroeconomic crisis in Indonesia affects short- and long-term nutritional outcomes. Chapter 3 (Essay 2) shifts the focus from macro-level to micro-level exposure, looking into the impact of marriage customs on the gendered differences in nutritional investment. Chapter 4 (Essay 3) examines a modern aspect of the nutrition transition, using the recent expansion of digital super app platforms that provide food delivery, ridesharing, and other daily life assistance in Indonesia from 2015 to 2018. The supplementary files for each empirical essay are listed in Appendix A-C. The last chapter discusses the contribution, policy implications, and avenues for future research.

Essay 1

2 Macroeconomic shocks and long-term nutritional outcomes: Insights from the Asian financial crisis

Abstract

Climate change, conflicts, pandemics, and other disruptive events can lead to shocks in people's incomes, prices, and access to food, with profound implications for nutrition and health. The short- and long-term effects of different types of shocks are not yet sufficiently understood. Here, we use data from Indonesia to analyze effects of the Asian financial crisis, which happened in the late-1990s, on nutritional outcomes. The crisis contributed to large temporary increases in rice prices with regional variation, which we exploit to estimate effects on child height-for-age z-scores (HAZ) and other anthropometric indicators. Panel data regression models with individual fixed effects suggest that the rice price inflation led to an average decrease in HAZ of 0.135 and an increase in child stunting by 3.5 percentage points, after controlling for confounding factors. These effects were more pronounced in urban than rural areas. Children with mothers that only have little education suffered over-proportionally. Beyond the immediate impacts, we examine long-term effects and find that individuals severely hit by the crisis during childhood remain shorter also during adulthood and are more likely to be obese. Our findings highlight the need for nutrition-sensitive interventions in national and global crisis response policies.

Keywords: child nutrition, food security, food price inflation, obesity, human capital, Indonesia

JEL Classification: I15, N950

This essay is published as: Elmira, E. S., & Qaim, M. (2025). Macroeconomic shocks and long-term nutritional outcomes: Insights from the Asian financial crisis. *Global Food Security*, 100900. https://doi.org/10.1016/j.gfs.2025.100900. I, Elza S. Elmira, was responsible for conceptualizing the research, analyzing and interpreting the data, and writing the paper with guidance and support from Matin Qaim.

2.1 Introduction

Over the last few years, the world has experienced several types of overlapping crises with profound implications for food security and nutrition. The COVID-19 pandemic has contributed to rising food prices, job and income losses, and thus higher poverty rates in many low- and middle-income countries (Headey et al., 2020; Osendarp et al., 2021; Saccone, 2021; Hawkes et al., 2022). The Russian invasion of Ukraine has led to further rising prices on international grain markets, causing hardships especially for people in import-dependent countries (UN, 2022). The situation was and is further exacerbated by other conflicts, trade disputes, and weather extremes, contributing to supply chain disruptions and food price inflation (Food Security Information Network and Global Network Against Food Crises, 2024). The frequency and severity of shocks will likely further increase, making it important to understand the immediate and long-term nutritional impacts and develop strategies to reduce the most negative effects.

Crop failures, local conflicts, and famines disrupt food supplies and are known to negatively affect nutrition, often with severe short-term increases in child stunting, underweight, and wasting (Akresh et al., 2011; Yamauchi and Larson, 2019; Woldemichael et al., 2022). For other types of shocks, such as macroeconomic crises, the evidence is somewhat less clear (Frankenberg et al., 1999; Block et al., 2004; Strauss et al., 2004; Akresh et al., 2011). While negative nutrition effects can be expected, these are sometimes difficult to identify because of potentially confounding factors and geographic differences. Crop failures and famines tend to disadvantage rural communities over-proportionally (Mu and Zhang, 2011; Gørgens et al., 2012), whereas financial crises and other macroeconomic shocks may have more severe implications in urban areas (Webb, 2010; Yamauchi and Larson, 2019). A few studies also find gendered differences in the effects of crises, depending on the context (Block et al., 2004; Akresh et al., 2011).

Here, we analyze the short- and long-term nutritional impacts of the Asian financial crisis, which hit many Southeast Asian countries in the late-1990s and led to major food price inflation and other socioeconomic disruptions (Pritchett et al., 2002). Given the availability of suitable data, we focus on Indonesia, which several previous studies did as well. Despite the scale of the crisis, previous studies found mixed effects on child malnutrition in Indonesia (Frankenberg et al., 1999; Block et al., 2004; Strauss et al., 2004). Block et al. (2004) found that rural children in Central Java who were conceived and born during the crisis experienced significantly higher anemia incidence rates than other children, even though they did not observe significant impacts on child anthropometric measures. Existing studies look at short-term effects, comparing child nutritional outcomes before and during or shortly after the crisis.[2] Also, previous analyses did not control for regional variation in crisis severity, which can play an important role in determining impacts (Friedman and Levinsohn, 2002). We add to the literature by using panel data models with individual fixed effects and considering regional variation in crisis severity to analyze short-term effects on child nutritional status. Furthermore, for the same children hit by the financial crisis, we also analyze long-term implications for anthropometric outcomes during adulthood.

The remainder of this article is organized as follows. Section 2 provides a short background on the Asian financial crisis in Indonesia. Sections 3 describes the data sources and statistical approaches of data analysis. Section 4 presents the results, whereas section 5 discusses the findings and policy implications.

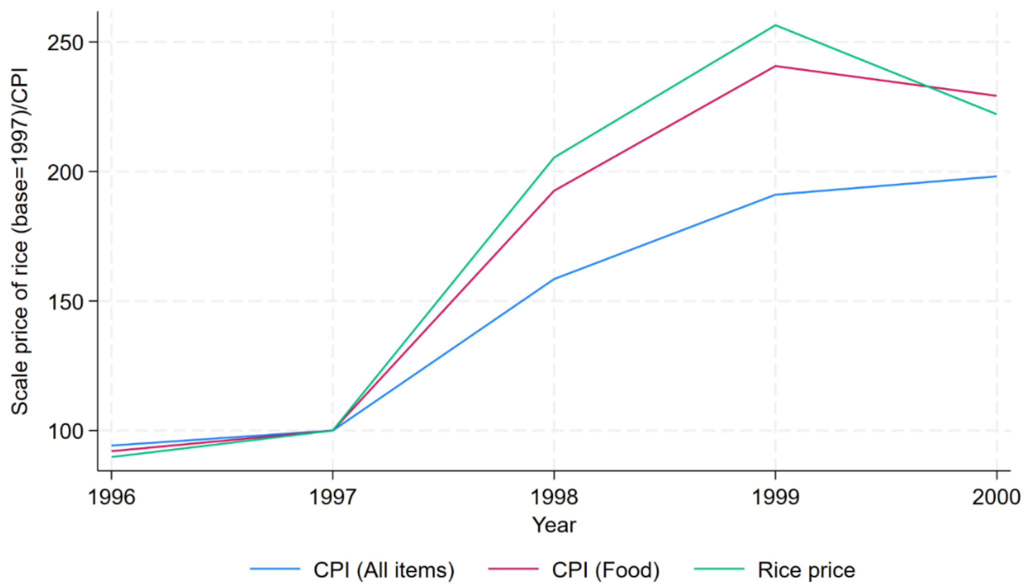
2.2 Financial crisis in Indonesia

The Asian financial crisis began in Thailand in the second half of 1997 with a collapse of the Thai baht. This led to a massive capital flight, triggering a chain reaction across Southeast Asia, including Indonesia. In January 1998, the Indonesian rupiah depreciated by about 400 %, followed by a decline in real wages of up to 40 % (Frankenberg et al., 2003). The combination of currency devaluation and substantial unhedged foreign-currency debt created widespread fear of a banking collapse in the financial and corporate sectors. This led the Central Bank of Indonesia to issue a blanket guarantee on inter-bank loans, which in turn tripled the money supply within a short period of time (Pritchett et al., 2002). The sudden expansion of the money supply and the currency depreciation affected domestic prices, leading to massive inflation. The financial crisis was exacerbated by droughts and forest fires in several Indonesian regions, contributing to crop production failures and further rising prices (Sharma, 2022). Food prices rose over-proportionally, causing street riots that eventually forced the Indonesian dictator, Suharto, to step down in mid-1998. The inflationary tendencies continued in 1999 and only weakened in 2000.

[2] While studies on the long-term nutrition impacts of other crises exist (e.g., Akresh et al., 2012; Gørgens et al., 2012; Zheng et al., 2012; Cui et al., 2020), we are not aware of studies on the long-term effects of the Asian financial crisis.

Rice is the main staple food in Indonesia, making up a large proportion of household expenditures (Frankenberg et al., 2003). Figure 2.1 shows the increase in rice prices and the consumer price index (CPI) in Indonesia between 1996 and 2000 at the national level. Between 1997 and 1999, rice and other food prices more than doubled. In 2000, food prices started to decline but were still at high levels, whereas the general CPI further increased. The pronounced effects of the financial crisis on rice prices and the strategic importance of this crop for food security in Indonesia mean that rice price variations can serve as a suitable proxy for the severity of the crisis, which we exploit below in our econometric analysis.

Figure 2.1 Trends in rice prices and CPI in Indonesia (1996-2000)



2.3 Materials and methods

To evaluate the short-term effects of the Asian financial crisis on nutrition, we develop models where we regress child nutritional outcomes on local changes in rice prices during the crisis, controlling for confounding factors. To evaluate long-term effects, we follow up the same sample of children into adulthood and estimate how their adult nutritional status is associated with rice price changes during the crisis period in the late-1990s. We first explain the data and the key variables of interest, before describing the estimation strategies in more detail.

2.3.1 Data

We use the Indonesian Family Life Survey (IFLS), a longitudinal household survey conducted by the RAND Research Institute in cooperation with different Indonesian Universities. IFLS covers 13 provinces in Indonesia following an initial sample of 7,224 households in 1993. Households were subsequently re-surveyed in 1997, 2000, 2007, and 2014. IFLS gathered comprehensive data on individual and household demographics, health, nutrition, and corresponding community conditions. The survey is representative of 83 % of the Indonesian population, with a total attrition rate of 13 % due to migration and death.

To measure the short-term effects of the Asian financial crisis on child nutrition, we use IFLS 1997 and 2000. IFLS 1997 provides insights into child nutrition as well as household and community conditions before the crisis hit, while IFLS 2000 reflects the post-crisis scenario, when the peak was over but prices were still relatively high. We follow up children who were aged 0-5 years in IFLS 1997 and compare their pre-crisis nutritional outcomes with the post-crisis situation as observed in IFLS 2000, when these children were 3-8 years old. The first years of life are the most critical for physical and cognitive development, and nutritional shortfalls in these critical stages typically result in stunted growth and other development impairments (World Health Organization et al., 2018). To evaluate the long-term effects of the crisis on nutritional outcomes, we follow up the same children in IFLS 2014, when they were young adults aged 17-23 years old. With 17 or 18 years, the final body height is typically reached, but effects of the crisis might still be visible, as stunted growth during critical childhood ages can often not be caught up later on.

2.3.2 Measuring nutrition outcomes

We use anthropometric measurements taken from individuals during the IFLS surveys and calculate common indicators of nutritional outcomes. For the analysis of short-term effects, we calculate height-for-age z-scores (HAZ) for children 0-8 years. HAZ is the most common indicator of chronic child undernutrition; it reflects nutritional quality, as linear growth is not only determined by food energy but also by the supply of various key micronutrients (Alderman and Headey, 2018). To reflect acute malnutrition, we also calculate weight-for-height z-scores (WHZ) for children 0-5 years aligned with WHO guidelines (World Health Organization, 2023). In addition, we calculate body mass index-for-age z-scores (BMIZ) and categorical indicators of nutritional status, namely stunting (HAZ<-2), wasting (WHZ<-2), overweight (BMIZ>+1), and obesity (BMIZ>+2). These indicators are calculated using WHO growth standards for children and adolescents (World Health Organization, 2009). For the analysis of long-term effects, we look at adult height, adult BMI, and overweight and obesity. Here, we use Asian cutoff values, namely a BMI>23 for adult overweight, and a BMI>27 for obesity (Roemling and Qaim, 2012).

2.3.3 Measuring the financial crisis

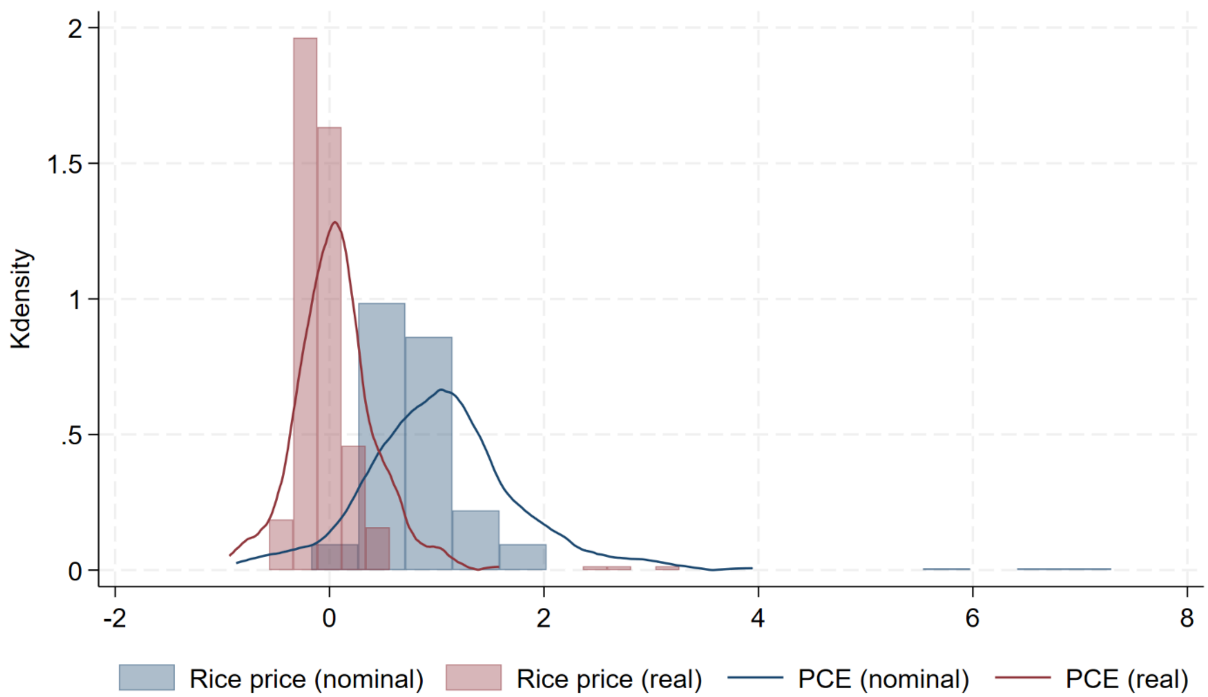
As explained, one of the main mechanisms through which households and individuals in Indonesia were affected by the financial crisis in the late-1990s was through rising food prices, and especially the price of rice, the country's main staple food. The IFLS include data on rice prices recorded at the community level during each survey wave. In particular, in each community the survey team collected prices on various rice qualities from different local retailers (traditional markets, minimarkets, grocery stores) and women community groups. We use these data to calculate community-level average prices of rice expressed in rupiah per kilogram for 1997 and 2000.

We use the difference in rice prices between 1997 and 2000 as our main variable to measure the crisis. Instead of the 2000 prices, it would actually have been preferable to use rice prices during the peak of the financial crisis in 1999. However, such data are not available from IFLS. As Figure 2.1 shows, national-level rice prices in 2000 were still significantly higher than in 1997, which we also confirm with the community-level IFLS data. Assuming that the prices observed in 2000 are sufficiently correlated with the unobserved prices at the peak of the crisis in 1999, we argue that the 1997-2000 price difference is a reasonable proxy of the crisis' severity, as experienced in each of the 312 communities covered by the IFLS.

We use two different measures, namely (i) the nominal rice price change and (ii) the real rice price change. The nominal price change appears more relevant as a crisis measure, as this is what households experienced in the short run; wages did typically not adjust at the same speed. However, other prices did adjust over time, so looking at both nominal and real price changes may be appropriate. The real price change is computed by deflating nominal prices using a Laspeyres-based CPI approach (Skoufias et al., 2000). This method incorporates the share of food and non-food expenditures into the CPI calculation. In doing so, we omit the rice expenditure from the calculation to avoid a potential upward bias in the CPI that could results from the rice price inflation during the crisis (see Appendix A1 in Appendix A for further details of the method).

Figure 2.2 shows the change in nominal and real rice prices and per capita household expenditures. While the nominal rice prices remained much higher in 2000 than in 1997 in almost all IFLS communities, the real prices had returned to pre-crisis levels in many of the communities. This drop in real prices after the crisis peak might reflect the impact of wage increases or also of government interventions, such as rice price subsidies and other social protection programs, including work creation programs and income transfers (Pritchett et al., 2002). However, Figure 2.2 also shows that in around half of the IFLS communities, real per capita household expenditures in 2000 remained below pre-crisis levels, suggesting that many households were still negatively affected by the crisis. Moreover, we see that in 30 % of the communities, the real rice prices in 2000 were still above their pre-crisis levels.

Figure 2.2 Change in nominal and real rice prices and per capita household expenditures (PCE) in IFLS communities (1997-2000)



While the rice price change between 1997 and 2000 at the community level is our main measure of the crisis's severity, we use another indicator for a robustness check, namely the direct response to the IFLS 2000 survey question whether or not the household had experienced a loss in income and/or employment during the crisis in 1998 or 1999.

2.3.4 Analyzing short-term effects

We analyze the short-term effects of the Asian financial crisis on child nutritional outcomes in Indonesia with panel data regression models of the following type:

$$N_{ihjt} = \beta_1(C_j \times T_t) + \gamma_1(X'_{ihj} \times T_t) + \lambda_i + T_t + \varepsilon_{ihjt} \qquad (2.1)$$

where N_{ihjt} is the nutritional outcome indicator (i.e., HAZ, WHZ, etc.) for child *i*, living in household h, in community *j*, at time *t*. We use the 1997 (pre-crisis) and 2000 (post-crisis) IFLS survey waves for estimation. C_j is the crisis indicator, which in most models is either the nominal or the real rice price change between 1997 and 2000 measured at the community level, as explained above. As C_j measures a change over time and therefore does not vary temporally within communities, we interact this variable with the year dummy (T_t). Community-level rice price changes are not influenced by individuals and therefore constitute a plausibly exogenous indicator of the crisis' severity at the local level. In a robustness check, we use the direct household response on loss of income/employment as an alternative crisis indicator.

X'_{ihj} in equation (2.1) is a vector of individual, household, and community controls measured at the pre-crisis baseline in 1997. This includes child sex and age, rural or urban location, parental education, religion, household wealth, and local infrastructure and policy conditions, among other factors.[3] We include pre-crisis and not current values because some of these factors might have been affected by the crisis, whereas our intention is to capture the crisis effect through C_j and control only for pre-existing differences. Without variation over time, X'_{ihj} would drop out when using a fixed effects estimator, which is why we interact the baseline values with T_t. Individual fixed effects are denoted by λ_i, controlling for unobserved time-invariant factors such as child care intensity, cultural habits, or genetics. Finally, ε_{ihjt} is an idiosyncratic error term.

The main coefficient of interest in equation (2.1) is β_1. We hypothesize that the financial crisis in terms of a strong increase in the local rice price has a negative effect on child nutrition, which would mean that β_1<0 for outcomes such as HAZ. However, for other outcomes, such as stunting

[3] Note that for age we also include a cubic function to account for possible non-linear relationships between child age and anthropometric outcomes.

we would expect β_1>0, as the crisis is hypothesized to increase the likelihood of child undernutrition.

For WHZ, BMIZ, and related outcome variables, β_1 could be both positive or negative, as these indicators consider the weight of the child in relation to its height. In very poor settings, a food price increase might imply that the child's energy intake would have to be reduced, such that both height and weight developments would suffer. However, in less poor settings rising food prices could also mean that households simply adjust their diets by reducing the consumption of more nutritious and expensive foods. Thus, children might still get enough food energy but would possibly suffer from protein and micronutrient deficiencies, which could be reflected in increasing weight and rising overweight/obesity. Note that overweight/obesity is not an indicator of the overconsumption of all nutrients, but of an intake of food energy that exceeds the body's energy expenditures.

In this connection we should mention that with our approach of comparing 1997 and 2000 prices and anthropometric outcomes we are not able to identify acute malnutrition impacts during the peak of the crisis. Hence, "short-term effects" in our context refers to effects on children during childhood ages (as opposed to long-term effects that persist into adulthood), not to immediate impacts on nutrition and health. Identification of the latter would require other types of data.

2.3.5 Analyzing heterogenous effects

Previous studies on the nutritional outcomes of various crises show that the effects may vary by age, gender, and socioeconomic status (Block et al., 2004; Akresh et al., 2011; Mu and Zhang, 2011; Gørgens et al., 2012; Cui et al., 2020; Woldemichael et al., 2022). This may also be the case here. To test this hypothesis, we estimate additional regression models with interaction terms as follows:

$$N_{ihjt} = \beta_1(C_j \times T_t) + \beta_2(C_j \times T_t \times X_{ih}) + \gamma_1 X'_{ihj} + \lambda_i + T_t + \varepsilon_{ihjt} \qquad (2.2)$$

where X_{ih} represents selected binary elements of the vector X'_{ihj} for which heterogeneous effects may be expected. We look at potential differences in terms of the sex and age of the child, maternal education, whether or not the household is poor,[4] and rural-urban residence. In equation (2.2),

[4] We use the official poverty line in Indonesia for the late-1990s (Widyanti et al., 2009).

coefficient β_1 captures the effect of the crisis on nutritional outcomes for the reference group (e.g., male children), β_2 tests whether the effect differs significantly between the two groups (e.g., boys and girls), while $\beta_1 + \beta_2$ measures the effect of the crisis on nutritional outcomes for the comparison group (e.g., female children).

2.3.6 Analyzing long-term effects

To analyze long-term nutritional effects of the crisis, we look at nutritional outcomes of adults who were affected by the crisis during critical childhood years. As adult and child anthropometric indicators cannot be compared in a meaningful way, we do not run panel data models but estimate cross-sectional models with lagged explanatory variables as follows:

$$N_{ihj}^{2014} = \beta_1 C_j + \gamma_1 X'_{ihj} + \lambda_r + \varepsilon_{ihdj} \quad (2.3)$$

where N_{ihj}^{2014} is the nutritional outcome (height, BMI, etc.) of adult *i* in 2014, referring to the same individual who was a child aged 0-5 years in IFLS 1997. In this analysis, we additionally include individuals who were in-utero or just born during the crisis (born in 1998-1999), as they may also have been affected by the crisis through the health and nutrition of their mothers. C_j is the change in the rice price between 1997 and 2000 in community j, and X'_{ihj} is the vector of baseline covariates, as defined above. Here, we additionally include baseline HAZ and regional fixed effects, λ_r, to control for potential unobserved differences.[5] If the financial crisis during childhood ages led to stunted growth, and this was not caught up during later years (e.g., adolescence), the individual may still be shorter than he/she would have been without the crisis, which would then be reflected in β_1<0 for the outcome of body height. We also test for heterogeneous effects of the crisis based on children's sex and cohort of exposure (in-utero/just born, 0-2 years, 3-5 years), maternal education, household poverty status, and rural-urban residence. As we cannot fully control for all potential sources of endogeneity in this cross-sectional specification, we only interpret these estimates as associations, not as causal effects.

[5] Note that for the in-utero and just born cohort, baseline HAZ is not available from IFLS 1997 data, as these children were not yet born in 1997. For this group, we use IFLS 2000 data to calculate baseline HAZ.

2.4 Results

2.4.1 Descriptive results

Table 2.1 shows descriptive statistics for the key variables used in our analysis. We follow up on the nutritional outcomes of approximately 2,100 children aged 0-5 years during IFLS 1997. At baseline, the mean HAZ was -1.73 and the stunting rate was 46 %, pointing at widespread child undernutrition. Nevertheless, 15 % of the children were overweight in 1997.

Table 2.1 Descriptive statistics of key variables

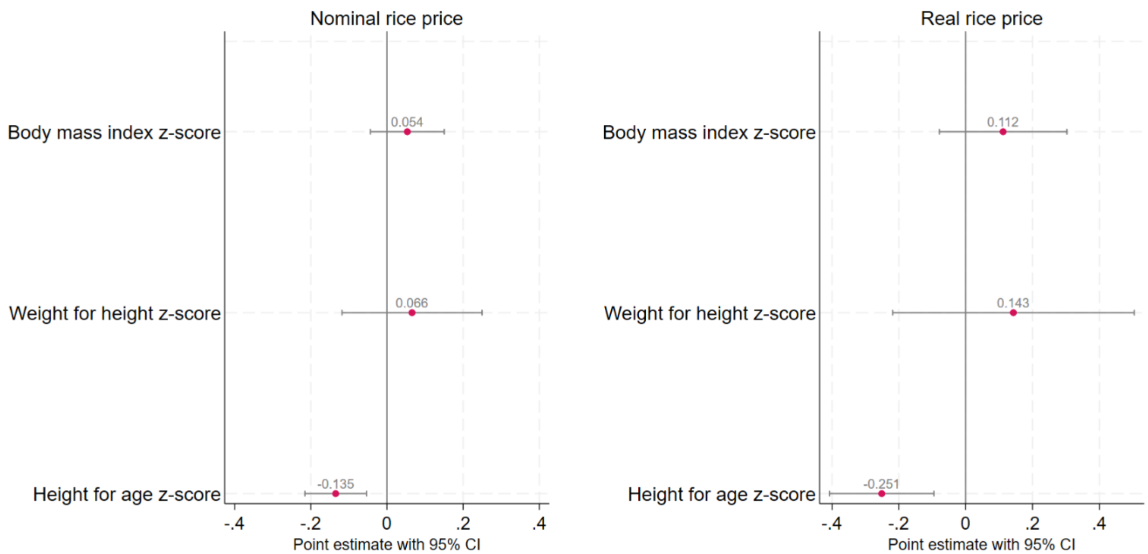
Variables	Observ.	Mean	Std. dev.	Min	Max
Summary statistics of outcomes in 1997					
Height-for-age z-scores (HAZ)	2,117	-1.73	1.66	-5.95	5.99
Weight-for-height z-scores (WHZ)	2,094	-0.42	1.39	-4.88	4.83
BMI-for-age z-scores (BMIZ)	2,104	-0.24	1.44	-4.97	5
Stunting incidence	2,117	0.46	0.5	0	1
Wasting incidence	2,094	0.10	0.31	0	1
Overweight incidence	2,104	0.15	0.35	0	1
Obesity incidence	2,104	0.06	0.24	0	1
Summary statistics of outcomes in 2000					
Height-for-age z-scores (HAZ)	2,412	-1.77	1.13	-5.83	4.28
Weight-for-height z-scores (WHZ)	955	-0.41	1.18	-4.92	4.75
BMI-for-age z-scores (BMIZ)	2,367	-0.47	1.10	-4.86	4.67
Stunting incidence	2,412	0.42	0.49	0	1
Wasting incidence	955	0.07	0.26	0	1
Overweight incidence	2,367	0.08	0.27	0	1
Obesity incidence	2,367	0.02	0.16	0	1
Summary statistics of crisis metrics					
Change in rice price (nominal)	2,112	0.83	0.67	-0.17	7.29
Change in rice price (real)	2,112	-0.06	0.34	-0.56	3.28
Income/employment loss in 1998-99	2,084	0.05	0.22	0	1

The lower part of Table 2.1 shows that the average change in the rice price between 1997 and 2000 was an increase of 83 % in nominal terms. As discussed above, nominal rice prices were still higher in 1999, with mean increases of more than 100 %, but detailed community-level price data are not available for 1999. The 1997-2000 mean price change expressed in real terms was close to zero, even though the standard deviations and minimum and maximum values underline considerable regional differences. Around 5 % of the households surveyed in 2000 reported that they suffered from income and/or employment losses during the 1998-1999 crisis period.

2.4.2 Short-term effects

Figure 2.3 shows the effects of changes in community-level rice prices on child HAZ, WHZ, and BMIZ, estimated with the models in equation (2.1). The rice price changes are expressed in terms of proportions, so a one-unit change is equal to a 100 % price increase. As discussed above, nominal rice price increases during the crisis were in the magnitude of 100 % or more.

Figure 2.3 Effects of rice price changes in 1997-2000 on child nutritional outcomes



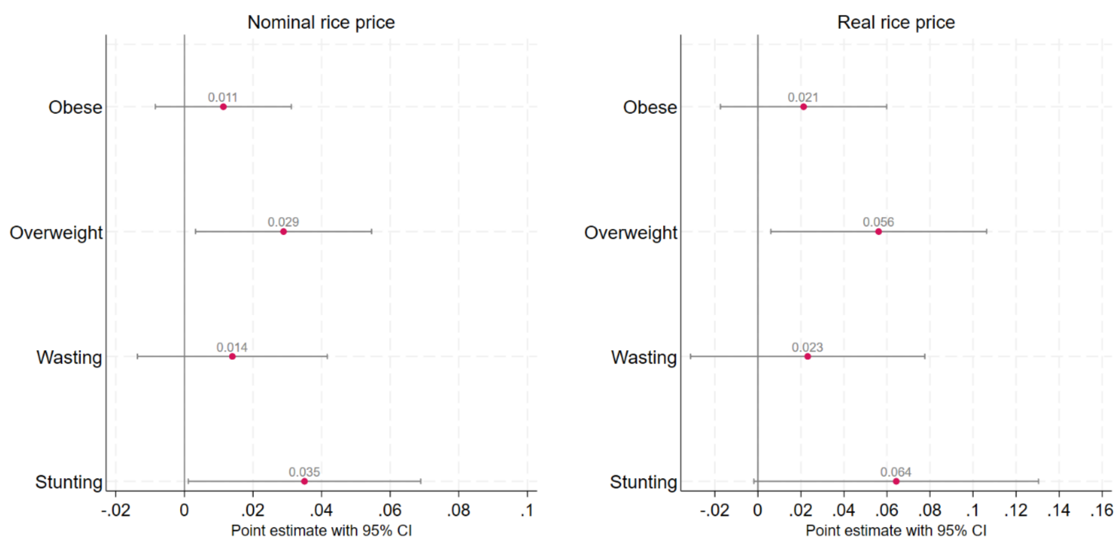
Note: Point estimates from fixed effects panel data regression models are shown with 95 % confidence intervals (CI). Full model results with all control variables are shown in Tables A1-A3 in the Appendix A.

The left panel of Figure 2.3 suggests that a 100 % increase in the nominal rice price has contributed to a 0.135 reduction in child HAZ, after controlling for other factors. This is a relatively large effect, which confirms that the financial crisis worsened the nutritional situation of children. The right panel of Figure 2.3 shows that negative child nutrition effects are also obtained when using the real price change as an explanatory variable. As one would expect, the negative effect of a one-unit price increase on HAZ is even stronger (-0.251) when the price change is expressed in real terms. For WHZ and BMIZ, we do not find statistically significant effects. WHZ measures acute malnutrition and is subject to high short-term variability during crisis periods. With our approach we are not able to identify acute malnutrition during the peak of the crisis. In contrast, HAZ is a cumulative measure of child undernutrition and therefore a more reliable indicator in our study.

To further test the robustness of these findings, we use our other crisis indicator, namely whether or not the household reported a loss of income/employment during the crisis period, expressed as a dummy. The results of these alternative models are shown in Table A1-A3 in Appendix A. They confirm the general finding that the crisis has contributed to a decrease in child HAZ. The income/employment loss variable has a coefficient of -0.22 in the HAZ model, which is statistically significant (Table A1 in Appendix A). At the same time, income/employment loss seems to lead to a 0.41 increase in BMIZ, which is also statistically significant (Table A3 in Appendix A). Possibly, income losses lead to dietary changes where more expensive nutrient-rich foods are substituted with cheaper calorie-dense foods, contributing to weight gains but lower dietary quality.

Figure 2.4 shows the estimation results from the models with binary indicators for child nutritional status as outcome variables. A 100 % inflation in the nominal rice price increases the rate of child stunting by 3.5 percentage points. At the same time, childhood overweight is increased by 3 percentage points, and this estimate is also statistically significant. These estimates suggest that child height was negatively affected by the crisis, whereas child weight was not, at least not such that it remained measurable in the year 2000, when the peak of the crisis was already over. Important to note is also that weight gains are possible at all life stages, whereas linear growth impairments during critical stages often result in permanent stunting. We obtain consistent results also when expressing the rice price change in real terms.

Figure 2.4 Effects of rice price changes in 1997-2000 on child nutritional status

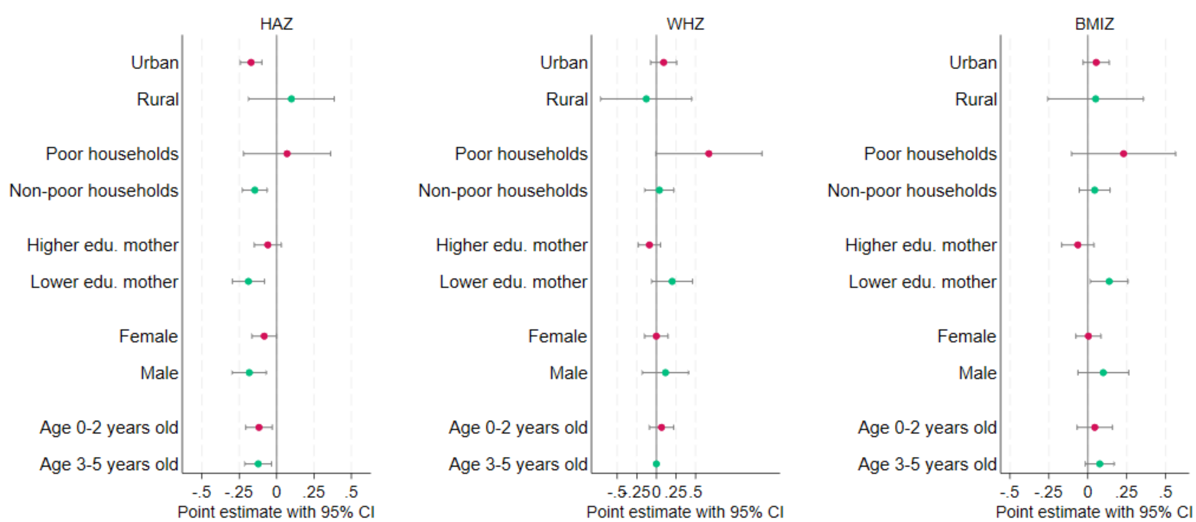


Note: Point estimates from fixed effects panel data regression models are shown with 95 % confidence intervals (CI).

2.4.3 Heterogenous effects

Figure 2.5 shows heterogeneous effects of the rice price changes on child nutritional outcomes for various population subgroups, estimated with the models explained in equation (2.2). Given the consistency of the estimates with nominal and real rice price changes, we here only report results for nominal price changes. For WHZ and BMIZ, the estimates are statistically insignificant for most subgroups. However, for HAZ, where many of the subgroup effects are significant, some interesting differences can be observed. Children in urban areas suffer more from the crisis-related rice price increase than children in rural areas, and this difference is statistically significant (Table A4 in Appendix A). This is not unexpected, since urban households rely more on rice purchases than rural households who often produce some of the rice consumed themselves. Additionally, children whose mothers only have a lower education (primary school or less) suffer more than children with better-educated mothers. Finally, boys seem to be more negatively affected than girls.

Figure 2.5 Heterogenous effects of nominal rice price changes in 1997-2000 on child nutrition



Note: Point estimates from fixed effects panel data regression models are shown with 95 % confidence intervals (CI). The subgroup differences are tested for statistical significance in Table A4 in Appendix A. WHZ can only be estimated among children aged 0-31 months old in 1997.

More surprising is that the negative effect of the crisis on HAZ is somewhat larger for children living in non-poor households than for children living in poor households. The difference between the two subgroups is not statistically significant (Table A4 in Appendix A), but intuitively we would have expected the opposite. That children in poor households did not suffer more may possibly be explained by social protection programs in Indonesia that are primarily targeted at poor communities and households. Earlier research suggests that supplementary feeding programs implemented during the crisis improved nutrition and reduced stunting among targeted children (Giles and Satriawan, 2015). These feeding programs could also be the reason for the seemingly positive effect of the crisis on poor children's WHZ (middle panel of Figure 2.5). In any case, our results suggest that a policy focus on poor households alone during crisis situations may not suffice to prevent negative effects on child nutrition.

Heterogenous effects of the rice price changes on child nutritional status are shown in Figure A1 in Appendix A. Consistent with the findings above, increases in child stunting and overweight are found for most of the subgroups. However, the point estimates between the different subgroups do not differ significantly (Table A5 in Appendix A), implying that here the effects are relatively homogenous.

2.4.4 Long-term effects

Figure 2.6 shows the estimates of the associations between rice price changes during the crisis (1997-2000) and later anthropometric indicators during young adulthood (measured in 2014), as explained in equation (2.3). A 100 % increase in the rice price during the crisis is associated with a decrease in adult height of 0.65 cm for the full sample, after controlling for confounding factors to the extent possible. This result suggests that individuals heavily affected by the crisis during early childhood years were not able to grow to their full height potential. Consistent results are also obtained when measuring the crisis in terms of real rice price changes (Table A6 in Appendix A).

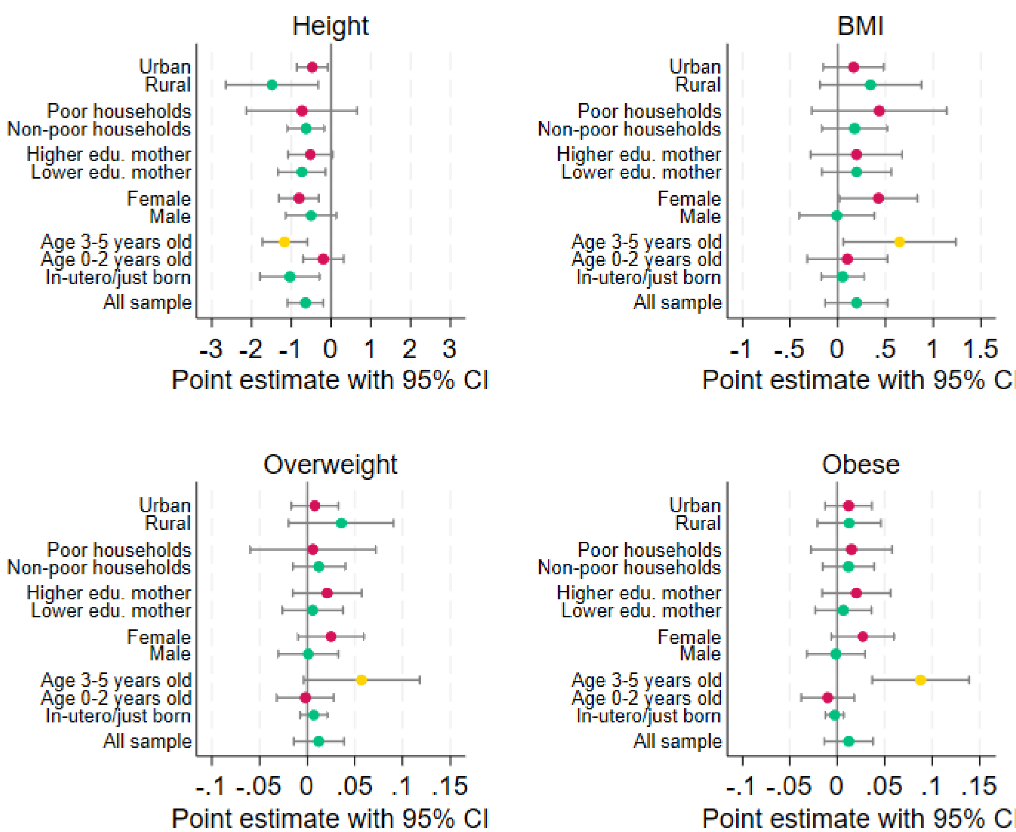
In addition to the full sample results, Figure 2.6 also shows estimates for various subgroups. Significant negative estimates for adult height are observed for most of the subgroups, including individuals in rural and urban areas and in poor and non-poor households. The negative association between the rice price increase and adult height is particularly pronounced for those who were 3-5 years old and those who were in-utero or just born during the crisis period,[6] underlining that there are different critical time windows for child development.

[6] For this cohort, height in IFLS 2014 is measured at ages 15–16. While individuals still experience height growth at these ages, they have passed the peak height velocity, and growth slows down (Kelly et al., 2014). Thus, height at 15–16 provides a close approximation to adult stature, although estimates for this group should be interpreted with caution.

Our finding of possible negative long-term effects for the in-utero and just born cohort align with Block et al. (2004), who showed severe short-run micronutrient deficiency among children conceived during the Asian financial crisis. The pronounced negative estimate for the 3-5-year cohort may reflect the fact that these children had less time for catch-up growth than those who were 0-2 years at the time of the crisis (Duflo, 2003; Akresh et al., 2012).

For BMI, and the likelihood of overweight and obesity, most of the estimates in Figure 2.6 have a positive sign but are not statistically significant. One exception is the group of those who were 3-5 years old during the crisis, for whom we find significantly positive associations with BMI and the likelihood of being obese. These results suggest that – for this group – the Asian financial crisis experienced during childhood may have contributed to stunted growth and obesity in adulthood.

Figure 2.6 Associations between rice price changes during the crisis and adult anthropometric outcomes in 2014



Note: Point estimates from OLS models with 2014 anthropometric outcomes as dependent variables are shown with 95 % confidence intervals (CI). Full model results with all control variables are shown in Table A6 in Appendix A. Subgroup differences are tested for statistical significance in Table A7.

2.5 Discussion

We have examined the effects of a major macroeconomic shock in Indonesia, the Asian financial crisis of the late-1990s, on nutritional outcomes among children, using panel data and regression models with individual fixed effects to control for potential unobserved confounding factors. We have also analyzed possible long-term effects by following up the same children into adulthood. One of the main mechanisms through which households and individuals were negatively affected by the crisis was the strong and rapid increase in the prices of food and other consumer goods, especially in 1998 and 1999. We use the increase in the rice price, which varied geographically based on exogenous factors, as our main indicator of the crisis' severity.

Four major findings shall be highlighted. First, children in communities with higher rice price increases have a significantly lower HAZ and are more likely to be stunted. Second, these negative effects of the crisis on child HAZ are more pronounced in urban than in rural areas, for boys than for girls, and for children with lower-educated mothers than for children with mothers that have higher education levels. Third, the crisis has increased the likelihood of childhood overweight. And fourth, the negative nutrition effects seem to have long-term consequences, as individuals who were particularly affected by the crisis during childhood ages remain significantly shorter also during adulthood. For the subgroup of individuals who were 3-5 years old during the crisis, we also observe a significantly higher BMI and likelihood of obesity during adulthood.

Our findings of negative child nutrition effects are consistent with previous studies that analyzed the impacts of different types of crises (Akresh et al., 2011; Yamauchi and Larson, 2019). However, for the Asian financial crisis in particular, earlier studies found no or only very limited impacts on child nutrition (Frankenberg et al., 1999; Block et al., 2004; Strauss et al., 2004). These earlier studies relied on descriptive comparisons of mean nutritional outcomes among children in the same age cohort before and after the crisis, without accounting for geographic variation in exposure. Not all regions and all children were affected to the same extent. Our approach accounts for this fact and thus provides more robust evidence of the crisis' effects on child nutritional outcomes. To our knowledge, long-term effects of the Asian financial crisis have not been evaluated previously.

Unlike drought and famine, which tend to predominantly affect rural areas (Akresh et al., 2011; Gørgens et al., 2012; Cui et al., 2020), the Asian financial crisis began in the financial and industrial sectors, affecting urban more than rural areas. Urban households are typically also more negatively affected by food price increases. Many rural households produce food themselves and are therefore better protected against high food price inflation (Headey et al., 2020). This likely explains why the negative effects on child HAZ are stronger in urban than rural areas.

Important to note is that we do not find significant difference in child nutritional impacts between poor and non-poor households. The Asian financial crisis led to price increases for all consumer goods and services (food, clothing, housing, health, etc.), thus constraining households across the income distribution (Friedman and Levinsohn, 2002; Levinsohn et al., 2003). That children in poor households did not suffer more may also be due to targeted social protection programs that the Indonesian government had implemented during the crisis, including supplementary feeding programs for undernourished children (Pritchett et al., 2002; Giles and Satriawan, 2015). While these programs seem to have been effective for those that were reached, our results suggest that a focus on poor households alone may not suffice to prevent negative child nutritional outcomes during crises.

Prior research shows that households often employ strategies to protect their children's consumption during crises, such as mothers reducing their own dietary intake (Block et al., 2004; Yamauchi and Larson, 2019). Our study adds to this by suggesting that higher maternal education offers a certain protective effect against the adverse effects of crises. Better-educated mothers may have more nutrition knowledge, which could help to maintain minimum dietary quality during critical child development stages. Moreover, higher maternal education is also a proxy for more female bargaining power within households and stronger community social capital, which can contribute to lessening the negative impacts of crises (DeLoach and Lamanna, 2011; De Silva and Sumarto, 2018).

Our findings on long-term effects suggest that crisis-related deprivation during critical child development stages can have lasting negative health consequences, including reduced adult height and elevated risks of obesity. That childhood stunting is associated with higher rates of overweight and obesity in adulthood has been pointed out in some previous studies (Gørgens et al., 2012; Zheng et al., 2012; Cui et al., 2020; Soliman et al., 2021). However, the findings on the stunting-obesity relationship are mixed; many factors play a role, including the timing of the crisis and the shape of post-crisis environments, among others (Adair et al., 2013; Chidumwa et al., 2020; Mani, 2012; Victora and Rivera, 2014). In any case, our findings suggest that at least some of the negative child nutrition effects of the Asian financial crisis have persisted into adulthood. More than 35 % of Indonesia’s adult population is currently classified as overweight or obese with further rising trends (UNICEF, 2022). While this is mainly due to a rapid nutrition transition that is not only observed in Indonesia but also in most other middle-income countries, our results indicate that the Asian financial crisis may have contributed to some extent.

In the light of the ongoing economic, environmental, and political crises globally, our study offers relevant policy insights for building more nutritionally resilient communities. Children exposed to crises during their formative years are more likely to suffer from malnutrition than unexposed children. The combined evidence shows that not all crises have the same impact on nutritional outcomes and that conducive socioeconomic and policy conditions can help to mitigate the worst outcomes. Early-life effects on nutrition can persist into adulthood, increasing the risk of obesity and non-communicable diseases later in life. These findings underscore the urgency of integrating suitable child nutrition interventions into crisis response policies to protect and enhance long-term population health and human development.

Essay 2

3 Marriage customs and nutritional status of men and women

Abstract

Malnutrition remains a serious problem. While various nutrition policies exist, these often fail to consider cultural factors. We contribute to the literature on culture and nutrition, focusing on gendered differences in nutritional investment. Using representative panel data from Indonesia covering a period of 21 years, we analyze how ethnicity-based marriage customs are linked to the body mass index (BMI) of men and women. Patrilocal practices are positively associated with male BMI and negatively associated with female BMI, suggesting discrimination against women. Matrilocal practices are positively associated with female BMI when comparing with women in other cultural settings, but not when comparing with men. The practice of bridewealth is positively associated with male and female BMI when comparing to individuals in settings without this cultural practice. Wherever positive associations between marriage customs and BMI are observed, these are largest for those already overweight, whereas the negative association been patrilocality and female BMI is most pronounced among women who are underweight. Our findings suggest that marriage customs may reinforce nutritional inequalities. A better understanding of such links in different cultural settings is important for effective nutritional policies, especially given that different malnutrition problems coexist in many countries.

Keywords: obesity, patrilocality, matrilocality, panel data, quantile regressions, Indonesia

JEL Classification: I15, J15, J16

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I, Elza S. Elmira, was responsible for conceptualizing the research, analyzing and interpreting the data, and writing the paper with guidance and support from the other two co-authors.

3.1 Introduction

Malnutrition comes in various forms, including undernutrition, micronutrient deficiencies, and overweight and obesity (FAO, 2024, Popkin et al., 2020, Swinburn et al., 2019, World Health Organization, 2016). In many countries, different forms of malnutrition coexist, contributing to high morbidity, mortality, large healthcare costs, and hampered economic and human development. Progress in reducing undernutrition and micronutrient deficiencies is currently too slow to meet the Sustainable Development Goal 2 targets; overweight and obesity are actually on the rise in most parts of the world, including low- and middle-income countries (FAO, IFAD, UNICEF, WFP WHO., 2024, Popkin et al., 2020). Malnutrition is determined by various economic and social factors. In addition, cultural factors can be important (UNICEF, 2020), but are often overlooked. Examples of cultural practices that may influence nutritional outcomes are kinship systems, son preferences, and marriage traditions, among others (Chakraborty and Das, 2005, Dasgupta, 2016, Rathore and Das, 2022). In this study, we link marriage customs – such as co-residence with parents/relatives after marriage and bridewealth – to the nutritional status of men and women to identify gendered differences in nutritional investment.

Marriage customs and other cultural practices can play an important role in terms of how food and other resources are distributed within the household. Often, discrimination against female household members is observed. This already starts at young ages, with girls in some cultural settings systematically receiving less nutritious foods and healthcare treatment than boys (Turner et al., 2021, Briones et al., 2018, Haddad et al., 1996). Female adolescents and adults additionally face risks of domestic violence, excessive workloads, early marriage, and high fertility, all of which can contribute to negative nutrition and health outcomes (Harris-Fry et al., 2017, Kunto and Bras, 2019, Lowes, 2020, Lowes and Nunn, 2017, Rathore and Das, 2022, Sear et al., 2002, Sear and Mace, 2008).

Many existing studies analyze links between marriage customs and gender inequality in terms of various economic and social dimensions, including education outcomes (Ashraf et al., 2020), employment (Rammohan & Johar, 2009), wages, and access to productive resources, pensions, and government transfers (Bargain et al., 2022, Bau, 2021; Collins, 2022). However, relatively few studies look at links between marriage customs and nutritional status. Some work exists on broader cultural practices, food consumption preferences, and the nutrition transition (Brown, 1991, Klaczynski et al., 2004, O'Dea, 2008). Several studies show that women in low- and middle-income countries are often more affected by overweight and obesity than men (Popkin et al., 2020, Roemling and Qaim, 2012), which is likely due to cultural restrictions that limit women's mobility outside the home (Ameye and Swinnen, 2019, Hansford, 2010, Wells et al., 2012). Moreover, women may have less control over household resources than men and experience long-term effects of childhood deprivation. The role of marriage customs in this connection is not yet well understood. A few studies analyze the role of son preferences and patrilineal kinship systems for gendered nutrition and health outcomes in different countries (Allendorf, 2013, Briones et al., 2018, Harris-Fry et al., 2017, Levine & Kevane, 2003, Lowes and Nunn, 2017, Lowes, 2020, Ren et al., 2014, Sear and Mace, 2008). The results of these studies are mixed, underlining that the effects are probably not uniform and depend on local conditions.

In this study, we focus on Indonesia, which is an interesting country to study links between marriage customs and gendered nutritional status for at least two reasons. First, Indonesia has been experiencing a profound nutrition transition over the last 25 years, with undernutrition still existing in some pockets but overweight and obesity rates rising rapidly (Popkin et al., 2020, Roemling and Qaim, 2012). Second, Indonesia is a culturally very diverse country with different ethnicities and local marriage traditions (Kunto & Bras, 2019). Among these are patrilocal and matrilocal co-residence customs, in which newlyweds live with the family of the groom or the bride, respectively. In patrilocal societies, men hold most of the power and control over resources, while women primarily handle domestic duties. A common practice in these societies is the payment of bridewealth, aiming to compensate the bride's family for the 'loss' of their daughter from the lineage group (Ashraf et al., 2020). Yet, bridewealth practices are not confined to patrilocal societies. In matrilocal societies, women can assume prominent economic roles and also enjoy inheritance rights (Bau, 2021). Such marriage customs are not unique to Indonesia but are observed also in many other countries and regions.

In particular, we aim to understand how the local marriage customs of patrilocality, matrilocality, and bridewealth correlate with the nutrition transition. Associations between marriage customs and the intra-household distribution of food and nutrition are likely established during childhood and are expected to extend into adulthood when individuals enter the marriage market. To evaluate associations between marriage customs and nutritional status, we focus on adults within the marriage age range and analyze their anthropometric outcomes. For adults, long-term panel data are available, which is of great advantage for the statistical analysis. We use data from the Indonesian Family Life Survey (IFLS), a longitudinal survey of more than 12,000 adults spanning the period from 1993 to 2014, and combine these with relevant ethnographic information. Panel data regression models with correlated random effects help us to reduce issues of endogeneity when estimating the associations between the various marriage customs and nutritional status in terms of men's and women's body mass index (BMI). BMI is the most widely used indicator of nutritional status among adults and reflects relevant longer-term nutritional conditions (Popkin et al., 2020, Tan, 2004). However, we acknowledge that BMI is an imperfect measure of all aspects of nutrition and discuss its limitations below.

The role of marriage customs may change over time with evolving socioeconomic conditions. Indonesia went through a massive economic transition during the study period, so we also analyze whether the associations between marriage customs and nutritional status show systematic time trends or differ between rural and urban areas. In addition, we use quantile regressions to test whether the associations differ across the BMI distribution. This is important because increases in BMI are positive for nutrition and health among underweight but not among overweight and obese individuals.

The results suggest that local marriage customs are significantly associated with nutritional status, potentially exacerbating obesity trends while discriminating against those particularly affected by undernutrition. Patrilocality is positively associated with male BMI, matrilocality is positively associated with female BMI, whereas bridewealth practices are associated with higher BMI for both men and women. However, within patrilocal populations, we observe discrimination against females, which is only partly alleviated by bridewealth practices. The observed associations are quite persistent over time. These results highlight the need for affirmative health and nutritional policies. Our findings align with previous studies suggesting that gender norms can be critical factors in the success of nutrition programs (Farnworth et al., 2023, Bonis-Profumo et al., 2021). Therefore, policies aimed at empowering women and strengthening their agency are important in contexts where marriage customs limit their autonomy. This presupposes a good understanding of the links between marriage customs and nutritional investments, to which our study attempts to contribute.

The rest of this article is organized as follows. In the next section, we discuss the theoretical concept explaining how marriage customs of patrilocality, matrilocality, and bridewealth may affect nutritional status. Section 3.3 describes the data and statistical methods used in the empirical analysis. The results are presented and discussed in section 3.4, while section 3.5 concludes.

3.2 Theoretical framework

To understand how marriage customs may affect nutrition, we build on established conceptual frameworks of asset transfers at the time of marriage (Fafchamps & Quisumbing, 2008). In many contexts, parents are deeply involved in the marriage decisions of their sons and daughters, partly also because these decisions can have long-term implications for their own economic and social situation either through co-residence or through transfers made between households and families. For a particular household, the utility function of parents regarding the decision to marry off their sons and daughters (U_p) can be defined as follows:

$$U_p = \left(A_\nu^f, A_\nu^m, sH_\nu^f, sH_\nu^m\right) + \omega_f U_f\left(A_\nu^f, \bar{A}_\nu^m, \gamma H_\nu^f, \gamma \bar{H}_\nu^m\right) + \omega_m U_m\left(A_\nu^m, \bar{A}_\nu^f, \gamma H_\nu^m, \gamma \bar{H}_\nu^f\right) \qquad (3.1)$$

where the superscripts f and m denote female and male children, respectively. A denotes asset provision at the time of marriage, and H denotes investments into the human capital of the children at the cost of s within marriage custom ν and a return on investment of γ. Human capital investments can encompass nutritious food, healthcare, education, and preventive measures, among others. $\bar{A}_\nu^f, \bar{H}_\nu^f, \bar{A}_\nu^m, \bar{H}_\nu^m$ represent the asset and human capital of their children's spouses, which can also influence the parents' decision to marry off their sons and daughters. ω denotes the welfare weight that parents assign to daughters and sons which could be associated with marriage market practices (i.e., bridewealth, dowry, bequests).

We are particularly interested in the local marriage customs of patrilocality, matrilocality, and bridewealth, all of which are common in Indonesia, depending on the ethnicity (Ashraf, 2009, Bau, 2021, Levine and Kevane, 2003, Lowes and Nunn, 2017, Rammohan and Johar, 2009). People belonging to patrilocal ethnicities, also known as virilocal, usually practice co-residence with the husband's side of the family after marriage. Examples include the Betawi, Banjar, and Manado ethnicities in Indonesia. People belonging to matrilocal groups (or uxorilocal) usually practice co-residence with the wife's side of the family after marriage. Examples include the Minangkabau, Toraja, and Bugis ethnicities in Indonesia. In ambilocal ethnicities, such as the Macassare, the newly married couple can choose whether to live with the husband's or wife's side of the family. In neolocal ethnicities, such as the Javanese, the couple lives separately from both the husband's and wife's side of the family after marriage (Rammohan & Johar, 2009). In Indonesia, neolocal ethnicities form the largest part of the population, whereas ambilocal ethnicities only make up less than 2 %. This is why we combine neolocal and ambilocal ethnicities for the statistical analysis. Patrilocal, matrilocal, and neo/ambilocal practices are mutually exclusive.

Bridewealth refers to payments from the husband's to the wife's family. The amount of the bridewealth varies and is typically negotiated case by case. This practice occurs across ethnicities and co-residence practices, even though it is more common in male-dominated communities. In some contexts, the practice of bridewealth is also referred to as 'bride price'. However, the term 'bridewealth' is usually preferred among anthropologists, as 'bride price' only narrowly describes the commercial transaction to compensate the bride's family for the loss of lineage and service (Tambiah et al., 1989). 'Bridewealth', on the other hand, extends beyond economic incentives and better represents the intentions of the groom's family to strengthen familial relationships and ensure the wellbeing of the bride and her offspring.

The different marriage customs can influence parents' decisions to invest in the human capital of their children. For instance, parents can receive support through co-residing with their children after the children's marriage or receiving assets from the groom's family, affecting future consumption. Assuming that parents maximize utility, we propose the following hypothesis about the relationship between co-residence practices and nutritional status:

Hypothesis 1: Nutritional investment in females is higher in ethnicities practicing matrilocality, while nutritional investment in males is higher in ethnicities practicing patrilocality. Post-marital residence patterns are associated with differences in BMI between female and male adults depending on location.

In predicting which household members would receive more nutritional investment based on marriage customs, we reflect on the solution for equation (3.1) where females and males would receive equal treatment if $\omega_f = \omega_m$ (Fafchamps & Quisumbing, 2008). Such symmetry is likely hard to achieve in cultural practices where the welfare weight is skewed towards the sons or daughters. Furthermore, the ratio of s and γ (cost of and return on human capital investment) determines parents' preference towards their female and male children in a given marriage market.

In reality, children are often treated differently where sons are favored in patrilocal and daughters face less discrimination in matrilocal systems.

Relying on the equilibrium concept of co-residence customs established by Bau (2021), we predict that $\alpha_{mat}^{f} - \alpha_{mat}^{m} \geq \alpha_{neo}^{f} - \alpha_{neo}^{m} > \alpha_{pat}^{f} - \alpha_{pat}^{m}$, where α^{f} and α^{m} are the shares of nutritional investment received by females and males in matrilocal, neolocal, and patrilocal ethnicities, respectively. One interesting question is what group to compare with. Do female (male) individuals in matrilocal (patrilocal) ethnicities only receive more nutritional investment and have higher BMI than female (male) individuals in other ethnicities or also more than the opposite sex in the same and other ethnicities? This question will be addressed empirically below.

Concerning the bridewealth customs, we propose the following hypothesis:

Hypothesis 2: The payment of bridewealth leads to higher nutritional investment in females. Bridewealth may attenuate discrimination against females.

Bridewealth primarily serves as compensation from the groom's to the bride's family in exchange for future service (i.e., labor force, human capital) and lineage provided by the bride (Fafchamps and Quisumbing, 2008, Lowes and Nunn, 2017; Tambiah et al., 1989). According to this theory, daughters possessing higher reproductive and human capital endowments can fetch a higher bridewealth upon marriage. Hence, we would expect that bridewealth practices may lead to increased nutritional investment in females and attenuate discrimination against them. However, the practice of bridewealth could also reinforce men's control over women, perpetuating a patriarchal system. In such a system, men may have more control over nutritional resources than men in less-patriarchal societies, so bridewealth may possibly also be associated with higher male BMI. There is a partial overlap between patrilocal societies and bridewealth customs. Nevertheless, bridewealth customs also exist in societies that are not patrilocal, so disentangling the effects of both marriage customs may be worthwhile.

In our third hypothesis, we aim to test whether the associations between marriage customs and nutritional status vary depending on the level of nutritional status:

Hypothesis 3: The associations between marriage customs and nutritional status vary across the BMI distribution, particularly at its extremes.

Previous studies by Jolliffe (2011) and Lakdawalla and Philipson (2009) suggest that the effects of various economic factors on nutrition are stronger at the tail ends of the BMI distribution. This is because the upper and lower tails represent more vulnerable population groups that could be more sensitive to changes in several explanatory variables. We are not aware of previous research that analyzes heterogeneous associations between local marriage customs and BMI, but we expect that different results at the lower and upper tails of the BMI distribution are likely.

3.3 Materials and methods

3.3.1 Data

This study relies on two main data sources: first, the IFLS panel data, and second, data on marriage customs from the Ethnographic Atlas 1967. The IFLS is a nationally representative longitudinal survey that was conducted in five waves, 1993, 1997, 2000, 2007, and 2014. The survey covers over 7,200 households in 13 provinces across the various Indonesian islands, representing 83 % of the population, only excluding the eastern parts of Indonesia (Strauss et al., 2016). We use an unbalanced panel, as the sample size grew over time to include new household members and split households. The survey collected information on individual health and anthropometric indicators, ethnicity, and a wide range of household and contextual socioeconomic variables. We use a total of 87,819 observations from adults 19-65 years old. Due to missing data, the actual sample for some parts of the analysis is smaller. In addition to the interviews and measurements at household and individual levels, IFLS also collected community-level data on demography, infrastructure, socioeconomic variables, and cultural practices in 321 enumeration areas through interviews with village leaders and other local experts.

The second data source, the Ethnographic Atlas 1967, compiles information on the traditional cultural practices of 1,291 ethnicities worldwide (Murdock, 1967). These data contain marriage customs information such as co-residence with parents after marriage and bridewealth customs, among other ethnographic details. This international dataset was validated by ethnographers globally and cross-referenced with similar studies on ethnicity practices in Indonesia. Marriage customs associated with each individual were identified by matching the ethnicity information from IFLS with the information from the Ethnographic Atlas. However, ethnicity information in the IFLS was only available from wave 2000 onward. Hence, we trace each individual from previous waves and assign them to the ethnicity information collected in 2000. For a few individuals who were no longer included in the 2000 wave, we assigned ethnicity information based on community details and the language in which the survey interviews were conducted.

3.3.2 Measurement of key variables

The main nutritional status variable used in our study is the BMI of male and female adults (19-65 years), which is based on individual weight and height measurements from the IFLS. Based on BMI, we categorize individuals into nutritional status groups, using World Health Organization recommendations for Asian populations, with cutoffs for overweight and obesity somewhat lower than for Western populations (Roemling and Qaim, 2013, Tan, 2004). We use the following groups and cutoffs: underweight, if the BMI is below 18; normal weight, if the BMI is between 18 and 23; overweight, if the BMI is above 23 (for Western populations, this cutoff is at 25); obese, if the BMI is above 27 (for Western populations, this cutoff is at 30).

Some discussion of the benefits and limitations of using BMI as a measure of nutritional status is warranted. An advantage of BMI is its being a comprehensive nutritional outcome measure that reflects energy intake, body energy expenditure, and general health conditions of adults. While BMI data are sometimes collected through self-reporting, in the IFLS, BMI calculations are based on actual weight and height measurements taken by survey assistants using calibrated weight scales and measuring boards. This method reduces the likelihood of measurement or reporting errors.

However, using BMI to categorize individuals as overweight or obese can be misleading, as the BMI does not consider body muscle mass and fat composition, which are relevant for evaluating obesity-related health risks (Cornier et al., 2011, Burkhauser & Cawley, 2008, Tan, 2004). Also, BMI is not a good indicator of nutritional quality because the consumption of essential micronutrients is not reflected in body weight. Dietary intake data are better suited to evaluate nutritional quality, but are not included in the IFLS (the survey includes data on household-level food consumption for all waves, but not on individual-level food intakes). However, it should be noted that dietary intake data – if available – typically refer to short recall periods and can therefore not reflect nutrition conditions in the past. Here, we are interested not only in the current nutritional intakes of adults but also in their nutrition conditions during childhood and adolescence, which are better reflected in BMI (Molini et al., 2010). To complement BMI, we also look at adult height separately. One disadvantage of using height in our analysis is that height hardly varies over time within individual adults, thus reducing the estimation efficiency in our panel data models. In summary, while BMI is not a perfect metric of nutritional status, it serves as an acceptable proxy for the purposes of our study, given its strengths, the limitations of available alternatives, and data availability constraints.

The main explanatory variables in this study are the marriage customs of patrilocality, matrilocality, and bridewealth. As mentioned above, these practices differ by ethnicity, so we use the ethnicity information from the IFLS to assign marriage customs to individuals. An alternative would have been to assign marriage customs based on the community that the individual lives in, as was done in previous research (Levine & Kevane, 2003). However, using community data may have two potential drawbacks. First, community data may be less precise than ethnicity data, because not all communities are ethnically homogenous. Second, if marriage customs are determined at the community level, they are closely (or sometimes perfectly) correlated with other community-level variables, which makes controlling for confounding factors in the regressions more difficult. This is why we consider ethnicity-based assignment of marriage customs preferable.

Nevertheless, one may ask to what extent traditional ethnicity-based practices are actually followed by people belonging to that ethnicity, because individual adherence to ethnicity-based traditions may change over time. Looking at actual co-residence and bridewealth practices of all individuals and households is not possible in our case, because these details are not available for the entire sample. Moreover, it could lead to serious endogeneity issues, because actual individual choices are likely correlated with unobserved factors that could also influence nutritional status. Fortunately, information about actual co-residence after marriage and bridewealth practices is available from IFLS for a subsample of married women and men. We use this subsample to show that ethnicity-based marriage customs are significantly correlated with actual practices, even after controlling for community-based practices (Table B1 in Appendix B), concluding that ethnicity-based marriage customs are valid explanatory variables in our context.

3.3.3 Regression models for estimating mean associations

We use panel data regression models of the following form to estimate associations between marriage customs and nutritional status:

$$Y_{i,e,t} = \beta_0 + \beta_1 MC_{e,t} + \beta_2 Female_{i,e,t} + \beta_3 MC_{e,t} \times Female_{i,e,t} + \gamma_1 X_{i,e,t}$$

$$+\gamma_2 Z_{c,t} + \gamma_3 T_t + \alpha_i + u_{i,t} \tag{3.2}$$

where $Y_{i,e,t}$ is the nutritional status variable of individual i (BMI, overweight/obesity status) belonging to ethnicity e at time t. $MC_{e,t}$ is a vector of the ethnicity-based marriage customs, patrilocality, matrilocality, and bridewealth. We conduct separate estimations for co-residence and bridewealth practices, as well as combined estimations to explore the interplay of these cultural factors. Additionally, we introduce an interaction term of the marriage customs with $Female_{i,e,t}$ to evaluate gendered differences. Thus, the association between marriage customs and nutritional status for men is characterized by the coefficient β_1 (in comparison to men in other ethnicities), the association for women is characterized by $\beta_1 + \beta_3$ (in comparison to women in other ethnicities), and the difference in the associations between men and women within the same ethnicity is characterized by β_3.

In these regressions, we control for individual and household characteristics, $X_{i,e,t}$, including years of schooling, employment status, urban versus rural residence, household size, per capita expenditure, and being Muslim. To control for lifecycle relationships between BMI and age, we also include age and age squared in the regressions. Furthermore, we include household food consumption variables, such as the share of staple foods, consumption of vegetable oil, and meat/fish. Food consumption habits and dietary preferences may be influenced by culture and ethnicity, meaning that some correlation with the marriage custom variables is possible. Note, however, that food consumption in the IFLS is measured at the household level, not the individual level. As we are particularly interested in understanding the associations between marriage customs and intra-household nutritional investment, controlling for household-level food consumption habits helps us to better disentangle the role of marriage customs from other cultural influences. As a robustness check, we also run the same regressions without including household-level food consumption variables.

Also, we control for community-level characteristics, $Z_{c,t}$, including road availability, access to clean water, electricity, healthcare centers, agricultural activities, wages in agriculture, population density, and school availability. Finally, we include a set of dummies for the survey waves, T. α in equation (3.2) is the individual-specific error term, whereas u is the unexplained variation of time t and individual i.

We will start with estimating the models in equation (3.2) with a random effects (RE) panel estimator. However, the RE estimator assumes that the individual-specific error term is uncorrelated with the explanatory variables, which is not necessarily the case due to possible unobserved heterogeneity. The fixed effects (FE) estimator is a solution to control for time-invariant unobserved heterogeneity, but it requires the explanatory variables of interest to vary over time. Our main explanatory variable of interest, $MC_{e,t}$, does not vary over time for individual i, meaning that the FE is not an option in our case. A suitable alternative is the correlated random effects (CRE) estimator, which controls for time-invariant unobserved heterogeneity without requiring all explanatory variables of interest to be time-variant (Wooldridge, 2019). This is achieved by including time-average effects of all time-variant explanatory variables as additional covariates. The CRE models are defined as follows:

$$Y_{i,e,t} = \beta_0 + \beta_1 MC_{e,t} + \beta_2 Female_{i,e,t} + \beta_3 MC_{e,t} \times Female_{i,e,t} + \gamma_1 X_{i,e,t}$$

$$+\gamma_2 Z_{c,t} + \gamma_3 T_t + \gamma_4 \bar{X} + \alpha_i + \varepsilon_{i,t} \quad (3.3)$$

where $\bar{X}$ is the vector of time averages for all the time-variant explanatory variables across the various survey waves.

3.3.4 Quantile regression models

The models in equations (3.2) and (3.3) estimate average associations between marriage customs and nutritional status for male and female individuals. Given the possibility of adverse health implications of both very low and very high BMI, it is of interest to analyze heterogeneous associations at the tail ends of the BMI distribution. We hypothesize that the associations of marriage customs with BMI are more pronounced at the tail ends of the distribution. We test this hypothesis by using unconditional quantile regressions (UQR) (Firpo et al., 2009). We first calculate the recentered influence function (RIF) of every τ-th quantile of Y (the BMI distribution), where for any given q_τ that is estimated using the unconditional sample analog of τ-th quantile, we use the density function $f_Y(\hat{q}_\tau)$ following the kernel method:

$$\widehat{RIF}\ (Y; \hat{q}_\tau) = \hat{q}_\tau + \frac{\tau - 1\{Y_i \leq \hat{q}_\tau\}}{f_Y(\hat{q}_\tau)} \quad (3.4)$$

We divide the τ-th quantile of the BMI distribution based on the nutritional status cutoffs for underweight, normal weight, overweight, and obesity (Jolliffe, 2011). Next, we estimate a regression model on the RIF estimates using CRE. Due to the complexities of incorporating the quantiles of the sums of the random variables in the estimation, we use a pooled OLS estimator combined with the Mundlak-Chamberlain device by adding $\bar{X}$ to the unconditional quantile regressions of BMI (Wooldridge, 2010).

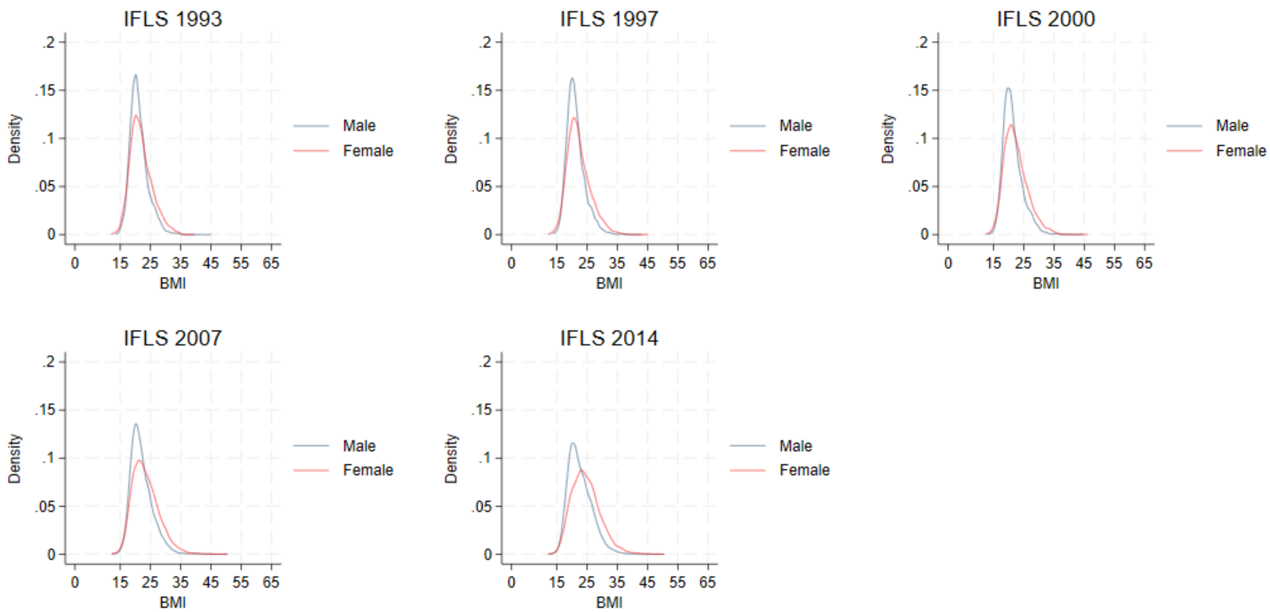
3.4 Results

3.4.1 Descriptive statistics

In examining the BMI distributions of adults in Indonesia between 1993 (wave 1 of the IFLS) and 2014 (wave 5), we find a considerable increase over time (Fig. 3.1). This increase is observed for both men and women, but it is more pronounced for women. Male mean BMI increased from 21.14 in 1993 to 22.63 in 2014; female mean BMI increased from 21.86 to 24.60 during the same period (Table B2 in Appendix B). In 2014, 41 % of the men and 60 % of the women were either overweight or obese. At the same time, 8 % of the men and 6 % of the women were still underweight in 2014.

The observed increases in BMI over time may be due to several factors, including changes in socioeconomic conditions and dietary patterns, but also the aging of the sample, given the typical positive association of age with BMI. To explore the role of age, we estimated polynomial regressions between BMI and age, confirming clear lifecycle patterns (Fig. B1 in Appendix B). BMI tends to increase with age at a diminishing rate, peaking at 54 years and declining afterward when using data from the entire panel, including all survey waves. The same general patterns are also found when looking at cross-section samples in individual survey waves (Fig. B1 in Appendix B). Strikingly, however, the BMI-age curves shift upwards over time, meaning that at each age level, the mean BMI in later survey waves was higher than in earlier waves. This underlines that factors other than age are also important for the observed changes in nutritional status between 1993 and 2014. As mentioned, we control for age and age squared in our panel data models, so the associations between marriage customs and nutritional status are to be interpreted net of any age effects.

Figure 3.1 BMI density functions for male and female adults in Indonesia (1993-2014)



Concerning ethnicity-based marriage customs, of all adults in our sample, 20 % belong to patrilocal, 10 % to matrilocal, and 70 % to neolocal (including ambilocal) ethnicities. Nineteen percent of the adults belong to ethnicities with bridewealth practices and 81 % to ethnicities without. Table B3 in Appendix B shows some differences in nutritional status between the cultural groups. The mean BMI for men is somewhat higher in patrilocal than in matrilocal and neolocal ethnicities. For women, the observed BMI differences between co-residence practices are small. For both, men and women, the mean BMI is higher in ethnicities with bridewealth practices than in those without.

Table B4 in Appendix B shows descriptive statistics of the other covariates that we use in the regression analysis, differentiating by ethnicity-based marriage customs. Individuals belonging to patrilocal ethnicities are somewhat better off than individuals belonging to other ethnicities in terms of higher mean education levels and per capita expenditures. There are also some differences in terms of food consumption patterns and other socioeconomic variables, but the magnitude of these differences is mostly small.

3.4.2 Mean associations between marriage customs and nutritional status

3.4.2.1 Associations of co-residence customs after marriage

We now estimate the panel data regression models explained in equations (3.2) and (3.3) above. We mostly rely on the CRE estimates from equation (3.3), as these better address endogeneity issues resulting from unobserved heterogeneity. The results are summarized in Table 3.1. Panel A of Table 3.1 shows the associations between the different co-residence customs and male BMI (coefficient β_1). As hypothesized, patrilocality is associated with higher male BMI. The CRE coefficient in column (3) suggests that patrilocality is associated with a 0.244 increase in BMI, after controlling for confounding factors. This is in comparison to men in neolocal ethnicities as the reference group.

Panel B of Table 3.1 shows the associations for women (coefficients $\beta_1 + \beta_3$). Patrilocality is not significantly associated with female BMI in comparison to women in neolocal ethnicities. However, in comparison to men, women in patrilocal ethnicities tend to have a 0.214 lower BMI (as shown in panel C, column (3), which represents the female interaction coefficient β_3). In contrast, matrilocality is not significantly associated with male BMI, but is associated with a 0.277 increase in female BMI in comparison to women in neolocal ethnicities. In matrilocal ethnicities, female individuals seem to receive the same nutritional investment as male individuals, as indicated by the statistically insignificant female interaction term for matrilocality in panel C. These gendered BMI associations support our first hypothesis that nutritional investment in females is higher in ethnicities practicing matrilocality, while nutritional investment in males is higher in those practicing patrilocality. These results also hold when excluding food consumption variables as household-level controls, as shown in Table B6 in Appendix B.

Table 3.1 Associations between ethnicity-based marriage customs and adult BMI

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Associations among men						
Patrilocality	0.268***		0.244***		0.175*	0.097
	(0.075)		(0.077)		(0.095)	(0.096)
Matrilocality	0.063		0.076		0.008	-0.013
	(0.095)		(0.097)		(0.105)	(0.106)
Bridewealth		0.151**		0.177**	0.124	0.204**
		(0.072)		(0.072)	(0.096)	(0.096)
Panel B. Associations among women						
Patrilocality	0.024		0.03		-0.188*	-0.233**
	(0.087)		(0.087)		(0.108)	(0.109)
Matrilocality	0.215**		0.277**		0.073	0.102
	(0.107)		(0.109)		(0.118)	(0.12)
Bridewealth		0.206**		0.245***	0.313***	0.388***
		(0.082)		(0.082)	(0.109)	(0.11)
Panel C. Difference between women and men (female interaction term)						
Patrilocality	-0.244**		-0.214**		-0.363***	-0.329**
	(0.108)		(0.106)		(0.135)	(0.133)
Matrilocality	0.152		0.201		0.065	0.115
	(0.142)		(0.141)		(0.157)	(0.154)
Bridewealth		0.055		0.068	0.188	0.184
		(0.108)		(0.107)	(0.143)	(0.142)
Panel D: Overall associations among adults (excluding female interaction term)						
Patrilocality	0.140**		0.132**		-0.018	-0.079
	(0.061)		(0.063)		(0.077)	(0.079)
Matrilocality	0.146**		0.186**		0.045	0.051
	(0.073)		(0.076)		(0.081)	(0.083)
Bridewealth		0.180***		0.213***	0.227***	0.304***
		(0.055)		(0.057)	(0.074)	(0.076)
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	22.412	22.35	22.412	22.35	22.412	22.412

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. Individual, household, and community control variables were included in the estimation, as shown in Table B5 in Appendix B. RE, random effects estimator. CRE, correlated random effects estimator.

In panel D of Table 3.1, we show alternative results of models that do not include female interaction terms, so here we cannot differentiate between effects for men and women. Although results suggest that both patrilocal and matrilocal practices are significantly associated with an increase in adult BMI, this is a misleading result because it masks the contrasting associations among males and females. Evidently, differentiating by gender is important when analyzing the implications of ethnicity-based marriage customs.

3.4.2.2 Associations of bridewealth practices

The associations between bridewealth practices and BMI are also shown in Table 3.1. Bridewealth practices are associated with a 0.245 increase in female BMI in comparison to women in ethnicities without such practices (Table 3.1, panel B, column 4). At the same time, bridewealth practices are also associated with a 0.177 increase in male BMI in comparison to men in ethnicities without such practices (panel A, column 4). As mentioned, bridewealth practices are conventionally observed in male-dominated societies where men's needs are prioritized over women's needs, which may explain the positive associations with male BMI. However, the female interaction term for bridewealth is not statistically significant (panel C), suggesting that the associations among male and female individuals are similar. As theorized above, bridewealth offers incentives for parents to invest more in their daughters to earn higher marriage payments, which can explain the positive association between bridewealth and female BMI. These findings support the first part of our second hypothesis, namely that bridewealth practices lead to higher nutritional investment to female individuals.

The second part of the second hypothesis is about bridewealth practices attenuating some of the effects of post-marital co-residence. To test this, we run additional models where we combine co-residence and bridewealth practices in the same regressions, as shown in columns (5) and (6) of Table 3.1. Again, we mostly rely on the CRE estimates in column (6). For men (panel A), both patrilocality and bridewealth have positive coefficients, but only the latter is statistically significant. This may be due to the positive correlation between patrilocal and bridewealth customs. In contrast, the coefficient for patrilocality becomes negative and significant for women (panel B), meaning that without bridewealth practices, patrilocality has a negative association with female BMI. This negative association is attenuated through bridewealth practices, indicated by the significantly positive coefficient for bridewealth in column (6) of panel B. Furthermore, we observe that the significant association between matrilocality and female BMI disappears after additionally controlling for bridewealth. These findings support the second part of our second hypothesis. Obviously, there are important interactions between co-residence and bridewealth practices.

We also ran the same regression models with adult height (instead of BMI) as an alternative outcome variable. These alternative results are shown in Table B7 in Appendix B. Many of the estimated coefficients are not statistically significant, which may be due to the lower data variation in the outcome variable: for individual adults, height hardly varies across the different survey waves. Patrilocality is associated with a slightly lower height in women, which is plausible. Somewhat surprising is that patrilocality is also associated with a slightly lower height in men and that bridewealth is associated with a lower height in women. However, all height associations are relatively small in magnitude (all well below 0.8 cm). Since body height is determined during childhood and adolescence, it is possible that the results would be different when using samples of younger individuals. Our analysis here is restricted to adults aged 19-65 years.

3.4.2.3 Associations with overweight/obesity

Patrilocal practices are positively associated with male BMI, matrilocal practices are positively associated with female BMI, whereas bridewealth practices are positively associated with both male and female BMI. However, a higher BMI is not necessarily better, especially not for people already affected by overweight or obesity. Using overweight as a binary outcome variable in the panel data regressions, we then analyze the extent to which different marriage practices may contribute to rising rates of overweight. The results are summarized in Table 3.2. Indeed, the CRE estimates in column (3) suggest that patrilocality is associated with a 2.8 percentage point higher likelihood of being overweight among men (panel A), whereas matrilocality is associated with a 4.6 percentage point higher likelihood of being overweight among women.

Bridewealth practices are associated with an increased likelihood of overweight among men by 2.4 percentage points and among women by 1.8 percentage points (column 4 of Table 3.2, panels A and B). The bridewealth associations with male and female overweight remain positive and significant when simultaneously controlling for co-residence practices (column 6). The patrilocality coefficient for men turns insignificant when controlling for bridewealth, while the matrilocality coefficient for women remains positive and significant. These estimates clearly suggest that matrilocality and bridewealth practices are positively associated with female overweight. The coefficients remain almost identical when household-level food consumption controls are excluded (Table B9 in Appendix B).

Table 3.2 Associations between ethnicity-based marriage customs and overweight

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Associations among men						
Patrilocality	0.054***		0.028***		0.028**	0.019
	(0.009)		(0.009)		(0.012)	(0.012)
Matrilocality	0.019		0.008		0.002	-0.002
	(0.012)		(0.012)		(0.013)	(0.013)
Bridewealth		0.022***		0.024***	0.013	0.022*
		(0.009)		(0.009)	(0.012)	(0.012)
Panel B. Associations among women						
Patrilocality	0.012		-0.008		-0.015	-0.02*
	(0.009)		(0.01)		(0.012)	(0.012)
Matrilocality	0.041***		0.046***		0.025*	0.024*
	(0.012)		(0.012)		(0.013)	(0.013)
Bridewealth		0.015*		0.018**	0.02*	0.028**
		(0.009)		(0.009)	(0.012)	(0.012)
Panel C: Difference between women and men (female interaction term)						
Patrilocality	-0.042***		-0.036***		-0.043***	-0.039**
	(0.013)		(0.012)		(0.016)	(0.016)
Matrilocality	0.022		0.038**		0.023	0.026
	(0.017)		(0.017)		(0.018)	(0.018)
Bridewealth		-0.007		-0.007	0.007	0.006
		(0.012)		(0.012)	(0.017)	(0.017)
Panel D: Overall associations among adults (excluding female interaction term)						
Patrilocality	0.017**		0.016**		0.005	-0.002
	(0.007)		(0.007)		(0.009)	(0.009)
Matrilocality	0.022***		0.024***		0.014	0.012
	(0.008)		(0.009)		(0.009)	(0.009)
Bridewealth		0.018***		0.021***	0.017**	0.025***
		(0.006)		(0.006)	(0.009)	(0.009)
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	.371	.365	.371	.365	.371	.371

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. Individual, household, and community control variables were included in the estimation, as shown in Table B8 in Appendix B. RE, random effects estimator. CRE, correlated random effects estimator.

3.4.3 Heterogeneous associations between marriage customs and BMI

In the previous subsection, we estimated average associations for the entire sample of male and female adults and the full period of observation. However, the associations may possibly vary for different subsamples and over time. In this subsection, we first differentiate by rural and urban locations, then we analyze possible changes over time, before we examine possible heterogeneity by nutritional status.

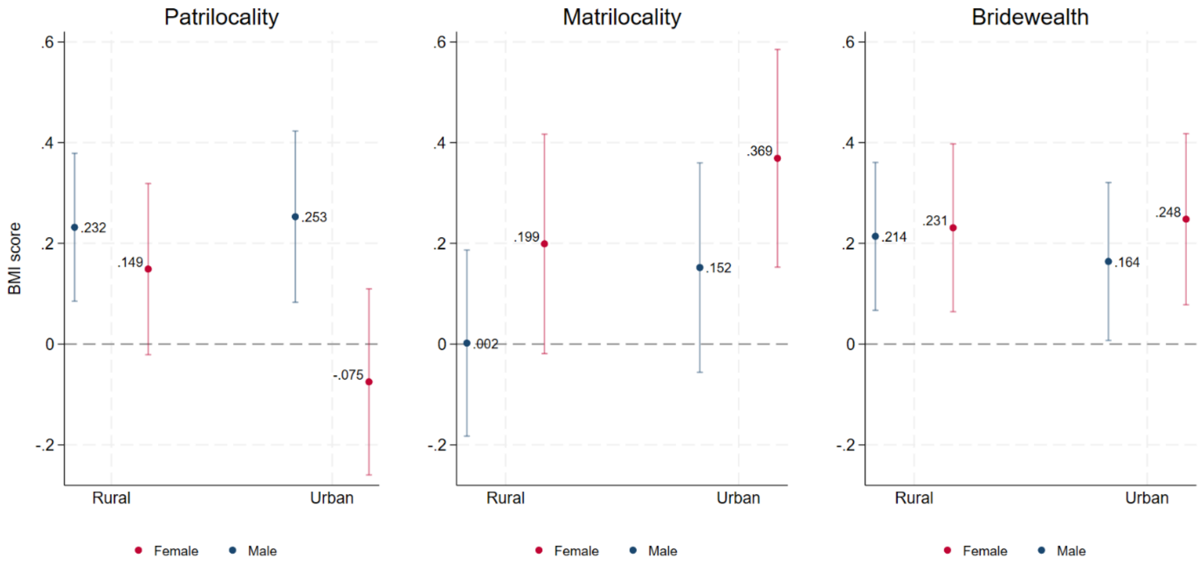
3.4.3.1 Possible differences between rural and urban locations

Rural households are often more traditional than urban households and adhere more strongly to ethnicity-based marriage customs. One may therefore assume that the associations between marriage customs and nutritional status are more pronounced in rural than urban areas. We test this assumption by running the same BMI models as above but also including an interaction term between the marriage customs and urban residence of the individual. Based on these estimates, we calculate separate associations for men and women in rural and urban areas, as shown in Fig. 3.2. As can be seen, the point estimates differ somewhat between rural and urban areas, but the hypothesis that the associations between marriage customs and BMI are consistently stronger in rural than urban areas is not supported. In other words, urbanization does not seem to weaken the links between marriage customs and nutritional status.

3.4.3.2 Possible changes over time

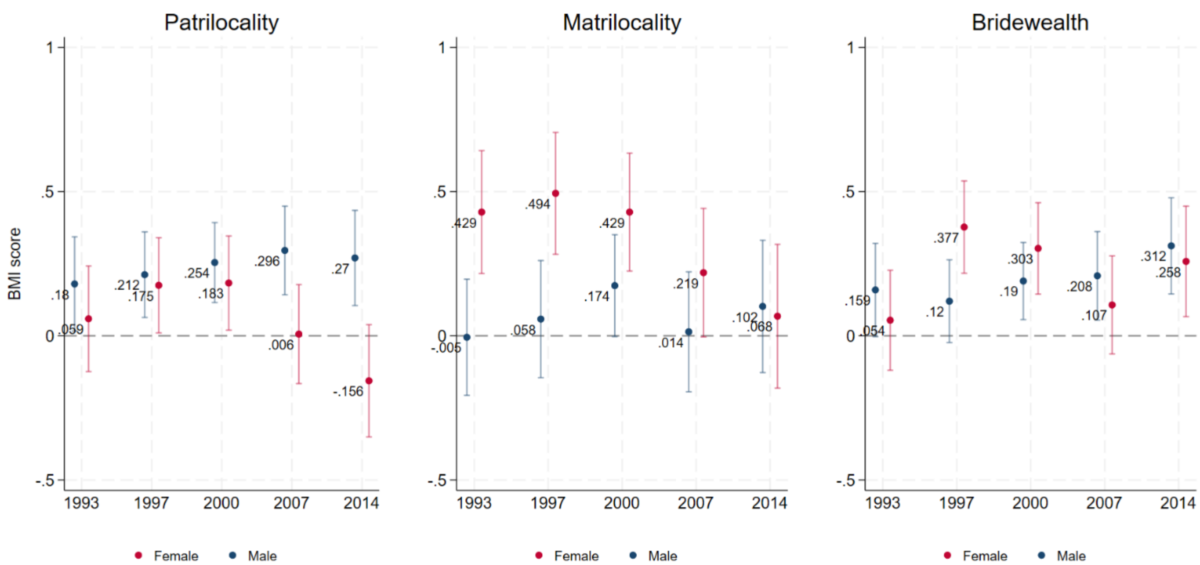
Cultural traditions often lose in importance over time with economic development and modernizing lifestyles. Against this background, one may assume that the associations between marriage customs and nutritional status shrink over time. We test this assumption by re-running the BMI models but this time including interaction terms between the marriage customs and the dummy variables for the different survey waves. Based on these estimates, we calculate separate associations for each survey wave, as shown in Fig. 3.3. For women, the positive associations between matrilocality/patrilocality and BMI seem to decrease over time. This may be related to loosening cultural restrictions for women and increasing physical mobility in modernizing societies (Rammohan & Johar, 2009). However, for bridewealth, such a trend over time is not observed for women. For men, some of the associations even seem to increase over time. In summary, many of the implications of marriage customs for nutritional status seem to persist over time.

Figure 3.2 Associations between marriage customs and BMI by rural and urban residence



Notes: Associations calculated from CRE models with interaction effects between marriage customs and urban residence. Point estimates with 90 % confidence intervals are shown. For details see Table B10 in Appendix B.

Figure 3.3 Associations between marriage customs and BMI over time

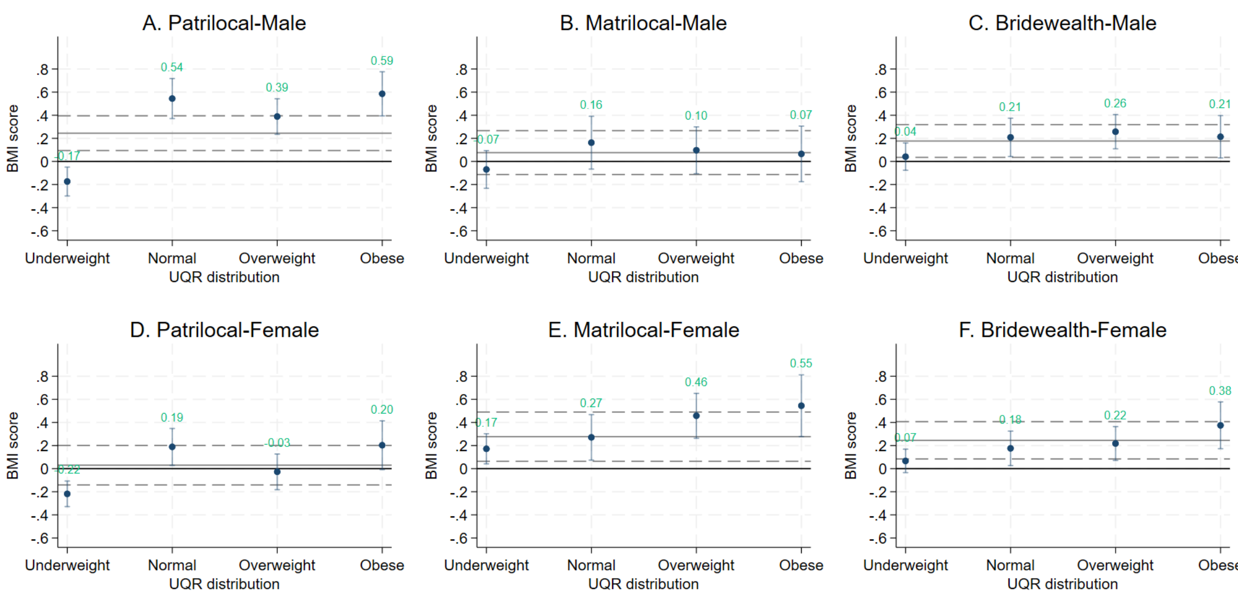


Notes: Associations calculated from CRE models with interaction effects between marriage customs and survey waves. Point estimates with 90 % confidence intervals are shown. For details see Table B11 in Appendix B.

3.4.3.3 Possible differences by nutritional status

The results so far referred to the associations between marriage customs and male and female BMI at the mean of the entire sample or of rural and urban subsamples. However, as mentioned already, an increase in BMI can be good or bad for health, depending on where on the BMI distribution an individual is located. Therefore, it is important to also examine how the relationship between marriage customs and nutritional status looks like at different points of the BMI distribution. As explained above, we use quantile regressions and evaluate effects for four different BMI groups, namely underweight, normal weight, overweight, and obese. Results are shown in Fig. 3.4.

Figure 3.4 Associations between marriage customs and BMI by nutritional status



Notes: Results from unconditional quantile regressions (UQR) with correlated random effects (CRE). Patrilocal and matrilocal practices were jointly included in the same regressions. Bridewealth effects were estimated with separate regressions (for joint estimates including all three marriage customs in the same regressions, see Fig. B2 in Appendix B). Point estimates with 95 % confidence intervals are shown. For comparison, the horizontal straight lines indicate the average CRE results from Table 3.1 (dashed lines above and below are 95 % confidence intervals).

Patrilocality is associated with an increase in BMI for normal weight, overweight, and obese men, but not for underweight men (panel A of Fig. 3.4). In fact, the increase is strongest for obese men, whereas for underweight men a slightly negative association (a BMI decrease of 0.17) is observed. For underweight women, patrilocality is also negatively associated with BMI (panel D). For normal weight women, the association between patrilocality and BMI is positive, whereas for overweight and obese women the associations are statistically insignificant. Matrilocality is not significantly associated with BMI among any of the male groups (panel B), but is positively and significantly associated with BMI among all female groups (panel E). Strikingly, the BMI association of matrilocality is smallest for underweight and largest for obese women. Similarly, bridewealth has the largest association with BMI among obese women, whereas among underweight women the association is small and statistically insignificant (panel F).

For men, similar distributional patterns of bridewealth are observed (panel C). These findings support our third hypothesis that the associations between marriage customs and nutritional status vary across individuals with differing nutritional status, especially when comparing the two ends of the BMI distribution. The large positive associations between some of the marriage customs and BMI among obese men and women, and the negative associations between patrilocality and BMI among underweight men and women, are particularly worrisome. Our findings imply that ethnicity-based marriage customs may further reinforce some of the malnutrition problems in Indonesia.

3.5 Conclusion and policy implications

3.5.1 Discussion

In this study, we have analyzed links between different marriage customs and nutritional status in Indonesia. In particular, we have examined associations between patrilocality, matrilocality, and bridewealth practices and male and female BMI. We have exploited panel data from adult individuals spanning a period of 21 years. Panel data regression models with correlated random effects have helped us to control for unobserved time-invariant heterogeneity.

The data from Indonesia reveal significant changes in the BMI distributions and nutritional status of men and women over the 21 years of observation. The BMI distributions notably shifted to the right, meaning that underweight decreased whereas overweight and obesity increased. The observed BMI increases are partly due to lifecycle patterns but are also driven by various other socioeconomics and cultural factors. Overweight and obesity rates are consistently higher among women than men, which is a common observation not only in Indonesia but also in most other low- and middle-income countries (Ameye and Swinnen, 2019; Popkin et al., 2020; Rachmi et al., 2017; Roemling and Qaim, 2012, Roemling and Qaim, 2013).

Four major findings confirm our hypothesized relationships between marriage customs and BMI. First, patrilocality is positively associated with men's BMI, while matrilocality is positively associated with women's BMI. Second, bridewealth practices are associated with a higher BMI among both men and women. Furthermore, when including all three ethnicity-based marriage customs into the same regressions, bridewealth practices attenuate some of the associations of patrilocality, because of a positive correlation between patrilocality and bridewealth practices. Third, the nutritional implications of all three marriage customs differ along the BMI distribution. The largest positive associations with BMI are observed among those who are already obese, whereas patrilocality is negatively associated with BMI among underweight men and women. Lastly, similar associations between marriage customs and BMI are observed across rural and urban locations and also over time, indicating the long-term and persistent links between traditional cultural practices and nutritional status.

Our results are consistent with existing theories of asset transfers at the time of marriage. Households tend to invest more in nutrition and health of the gender that will bring the most assets according to local marriage customs, as this maximizes the return to the parents in the households via transfers or care work in old age. The first main result supports this theory by showing that the practice of co-residence with the husband's parents (patrilocality) is associated with a higher BMI among men compared to men from neolocal societies. These results align with previous studies analyzing the gendered effects of marriage customs on other wellbeing outcomes. In patrilocal cultures, parents are more likely to invest their resources in sons, as they are typically more dominant economically in these cultural settings. This investment is often seen as a contribution to the lifetime resources of the parents and a form of old-age insurance (Dasgupta, 2016; Rathore and Das, 2022). Patrilocality may lead to discrimination against girls and women in some situations, as our results suggest and as previous studies have also shown (Allendorf, 2013; Bargain et al., 2022; Bau, 2021; Briones et al., 2018; Collins et al., 2022; Dasgupta, 2016; Harris-Fry et al., 2017; Rammohan and Johar, 2009; Sear and Mace, 2008). Bridewealth practices can attenuate this discrimination to some extent.

Our results differ from a previous study that examined links between co-residence after marriage and children's nutritional status in Indonesia, namely, Levine & Kevane (2003), who found that sending daughters away for marriage (patrilocality) did not lead to parents investing less in girls than boys. There are two possible reasons for the different results. First, Levine & Kevane (2003) used community survey data to determine marriage customs, whereas we use the individual's ethnicity, which we feel is more reliable and less prone to measurement error.[7] Second, while Levine & Kevane (2003) used anthropometric data from male and female children, we use anthropometric data from male and female adults. It is possible that marriage customs have different nutritional effects across the lifespan, with discrimination against females becoming more pronounced when adolescents enter the age of marriage and/or productive work (Sraboni & Quisumbing, 2018).

We also found that co-residence with maternal parents (matrilocality) is associated with a higher BMI among women compared to women from other co-residence cultures. This aligns with previous studies indicating that matrilocality influences investment in female household members, as parents consider their daughters as a kind of old-age insurance (Bau, 2021; Lowes, 2020; Sear et al., 2002; Sear and Mace, 2008). However, after controlling for bridewealth the significant association between matrilocality and female BMI disappears, suggesting that bridewealth practices are more strongly associated with female nutritional status than matrilocality.

Bridewealth practices are associated with higher BMI for male and female individuals and attenuate some of the effects of co-residence practices. For women, the result can be explained by parents expecting a higher bridewealth payment when their daughter is well nourished and healthy (Ashraf et al., 2020; Bau, 2021; Lowes and Nunn, 2017), leading to larger nutrition and health investment to female individuals. This is in line with previous work in Indonesia and Ghana showing that bridewealth practices have positive effects on female education (Ashraf et al., 2020; Lowes and Nunn, 2017). However, a nuanced interpretation is required. In some situations, bridewealth practices can also have negative effects on females through increasing domestic violence, early marriage, or high fertility during times of economic shocks (Corno et al., 2020; Lowes and Nunn, 2017).

For men, the positive association between bridewealth practices and BMI may be unexpected. However, this association is not in comparison to women in bridewealth-practicing ethnicities but to other men in ethnicities without bridewealth practices. Bridewealth practices are often associated

[7] Community survey data rely on the answers of village leaders who may not always have perfect and reliable information on the marriage customs of all families in the community. In exploring the IFLS community survey data, we found some surprising patterns and unrealistic changes over time. For example, the 1997 community survey data suggest that the majority of the study areas practiced matrilocality (46.3%, much higher than in the Ethnographic Atlas data), whereas the 2007 community survey data suggest that the majority of the areas practiced neolocality (66.5%).

with a stronger patriarchal system, allowing men to exert more control over household resources. In such patriarchal societies, it is likely that male individuals obtain greater investment in nutrition and health than in other societies. This pattern should therefore not be overinterpreted as a net effect of bridewealth practices.

Ethnicity-based marriage customs benefiting specific genders have long-standing historical roots. Historically, receiving more food meant being better nourished and healthier. In the context of the more recent nutrition transition, with rapidly rising overweight and obesity rates, this is no longer the case. Nowadays, receiving consistently more food because of traditional marriage customs can contribute to overweight and obesity, as our results also underline. Patrilocality is positively associated with overweight among men, matrilocality is positively associated with overweight among women, and bridewealth practices are positively associated with overweight among both men and women. Our quantile regression results show that these positive associations are largest at the upper end of the BMI distribution. At the same time, patrilocality is negatively associated with BMI among underweight men and women. These findings suggest that marriage customs may further reinforce some of the nutritional inequalities in Indonesia.

We have also used the panel data to analyze possible differences between rural and urban areas and between the different survey waves. While small differences were identified, the results overall suggest that the associations between marriage customs and BMI persist over time. This is in line with Buttenheim & Nobles (2009) who found that ethnicity-based cultural norms and their effects are often persistent even as societies rapidly develop economically.

3.5.2 Policy implications

The findings from this study have significant implications for public health and nutritional policies in Indonesia and other countries with similar cultural backgrounds. The findings clearly show that patrilocality, matrilocality, and bridewealth practices are significantly associated with changes in BMI and nutritional status. In particular, the estimates suggest that these marriage customs may exacerbate overweight and obesity trends while compounding the effects of undernutrition. It is unlikely that ethnicity-based marriage customs can be abolished or modified effectively simply by legislation. Hence, it is even more important to address nutritional problems and inequalities through policy interventions that explicitly consider gender roles within traditional marriage customs. For instance, nutrition interventions specifically targeted towards women and girls in cultural settings where they are disadvantaged could help to close the observed gender gap in nutritional investment (Quisumbing et al., 2021).

However, targeting nutrition interventions to women and girls alone neglects the reality that men and boys also have unhealthy diets and experience rising rates of overweight and obesity. Nutritional awareness and affordable access to healthy diets need to be promoted more universally. Understanding how marriage customs are associated with gender differences in nutritional status can be instrumental in tailoring interventions to specific local contexts. Nutrition training programs are often designed only for women. Yet, the literature suggests that involving men and village leaders can enhance the effectiveness of such initiatives and also promote women's participation in household decision-making (Ahmed et al., 2023; Farnworth et al., 2023; Bonis-Profumo et al., 2021).

Social and behavioral change communication (BCC) initiatives aimed at promoting equal treatment and improving dietary quality for male and female individuals, targeting families and schools, could be particularly effective in promoting better nutrition. Such initiatives also need to engage men, as traditional gender roles and gendered patterns of resource distribution are unlikely to change without behavioral change among both men and women. BCC may eventually also help to weaken the role and impact of traditional marriage customs on differential investments in sons and daughters.

As societies modernize, gender roles are often gradually becoming more equal, such that discriminatory effects of cultural practices on women's wellbeing tend to decrease (Bau, 2021; Rammohan and Johar, 2009). However, our findings suggest that such processes of cultural change are slow. Enabling policies – such as improved access to childcare and flexible working environments – can help improve women's wellbeing and economic opportunities in all cultural settings, independent of ethnicity-based marriage customs. Efforts to promote women's empowerment and education are also important, as empowered women are better able to advocate for their needs, especially in cultural contexts where they may otherwise be disadvantaged. However, such policies must also consider potential tradeoffs between women's economic and reproductive roles. For instance, while female labor-force participation may contribute to greater female financial autonomy, it may also increase women's workload, with possible negative effects on women's own health and wellbeing (Mehraban et al., 2022; Quisumbing et al., 2021). Mitigating policies need to be tailored to the specific local conditions.

In conclusion, research and policy-making for improved nutrition should consider the role of culture and marriage customs more explicitly. More research in different cultural contexts is needed to gain a better understanding of the multifaceted relationships and develop best practices for suitable interventions.

Essay 3

4 The impact of super apps on the nutrition transition in low- and middle-income countries: Evidence from Indonesia

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. We exploit the staggered rollout of Gojek and Grab between 2015 and 2018 in Indonesia to estimate their effects on nutritional and dietary outcomes, combining super app expansion data with Indonesia's Basic Health Survey (Riskesdas) and the National Socioeconomic Survey (Susenas). We incorporate baseline covariates using a doubly robust difference-in-differences approach to tackle endogeneity issues. The results show that super apps increase BMI, which adversely affects the incidence of overweight and obesity. The effect is more pronounced in cities and districts with online food delivery features. These apps disproportionally increase BMI among individuals who are already overweight/obese, younger, and more affluent (i.e., higher education, higher income, in employment), indicating higher usage among these groups. This is due to increased consumption of unhealthy food (i.e., salty and prepared foods). On the other hand, super apps have the potential to reduce underweight and improve dietary diversity. 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 Classification: I12, I15, O15, O33

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4.1 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 low- and middle-income countries (LMICs) (Brouwer et al., 2021). Additionally, the digital transformation of the food system exacerbates the rise in non-communicable diseases by discouraging active lifestyles and promoting unhealthy diets (Popkin, 2017, Bennett et al., 2024). Novel aspects of this transformation, including digital platforms, modern marketing, and access to out-of-home food, remain underexplored (Andreyeva et al., 2011, Granheim et al., 2022). The rise of on-demand companies offering services such as food delivery, ride-hailing, and e-commerce (also known as super apps) may improve convenience and access to goods, but can also encourage unhealthy lifestyles and diets (Maimaiti et al., 2018, Horta et al., 2022). This study aims to address this issue by investigating the effect of super apps on nutritional outcomes and food consumption.

While earlier studies focus on the characteristics of super app users, the broader nutritional impacts and underlying pathways in the nutritional transition are less understood. Users of these platforms are described as younger, more affluent, and more sedentary, due to high work demands (Dana et al., 2021, Dominici et al., 2021, Keeble et al., 2021, Safira and Chikaraishi, 2022). These platforms typically offer food with lower nutritional quality (Meemken et al., 2022), which may increase unhealthy food consumption and worsen nutritional outcomes (Meemken et al., 2022). However, as most of these studies are correlational, the effects of digital platform exposure on otherwise healthier individuals remain unclear.

This study draws on the food environment construct developed by Turner et al. (2018), which highlights domains shaping how people acquire and consume food. We argue that the digitalization of food systems affects the accessibility, affordability, convenience, and desirability of unhealthy food. First, digital food services encourage food outlets' expansion in "food deserts", where there is limited healthy food supply (Brandt et al., 2019, Keeble et al., 2022, Bennett et al., 2024). Second, excessive in-app advertising of processed and junk food, such as pizza, sandwiches, sugar-sweetened beverages, ice cream, and salty packaged snacks, may exacerbate unhealthy diets (Andreyeva et al., 2011, Horta et al., 2022). These apps also ensure convenience and accessibility, especially for working individuals (Maimaiti et al., 2018, Dana et al., 2021, Dominici et al., 2021, Safira and Chikaraishi, 2022), but in doing so, may encourage greater consumption of such foods, increasing the risk of overweight and obesity.

On the other hand, digital technology also has a role in improving food security through increased access to and information on diverse diets (Pearson et al., 2014, Brandt et al., 2019, Bennett et al., 2024). Additionally, strategies to ensure consumer loyalty, such as discounts and price reduction strategies, enable the poorer groups to access more diverse food products (Nguyen et al., 2019, Tong et al., 2020). Merchants of fast food outlets connect their small-scale businesses to super apps as a means to improve their living conditions. Previous studies confirm this hypothesis by showing increased income among drivers and merchants, highlighting the potential to improve food security (Berger et al., 2018, 2019).

We examine the effect of super apps on nutritional outcomes by exploiting the staggered rollout of Gojek and Grab, the two largest digital platforms in Indonesia, from 2015 to 2018. A difference-in-differences approach is used to compare the nutritional outcomes between districts with and without super apps. Outcomes estimated include Body Mass Index (BMI, weight divided by height), waist circumference, nutritional status (i.e., overweight, obesity, underweight), and expenditures on different food groups. We then conduct heterogeneous treatment effect analyses across districts with varying socioeconomic profiles. Finally, we run individual-level analyses to assess variation across BMI distribution and population sub-groups.

Our findings show that super apps increase BMI and overweight/obesity incidences. The impact is more pronounced in cities, high-GDP districts, and those with an online food delivery feature. Individuals with above median income, at least junior high education, and employment experience greater BMI increases and a higher likelihood of being overweight or obese. Those with initially higher BMI also experience larger increases. While super apps do not affect physical activity, they do contribute to changes in food consumption. We observe increased food expenditure, macronutrient intake, and consumption of salty and prepared foods.

The rest of this article is organized as follows. The next section describes the profile of Gojek and Grab super apps. Section 4.3 details the data and statistical methods used in the empirical analysis. The results are presented in Section 4.4, followed by the discussion and policy implications in Section 4.5 and the conclusion in Section 4.6.

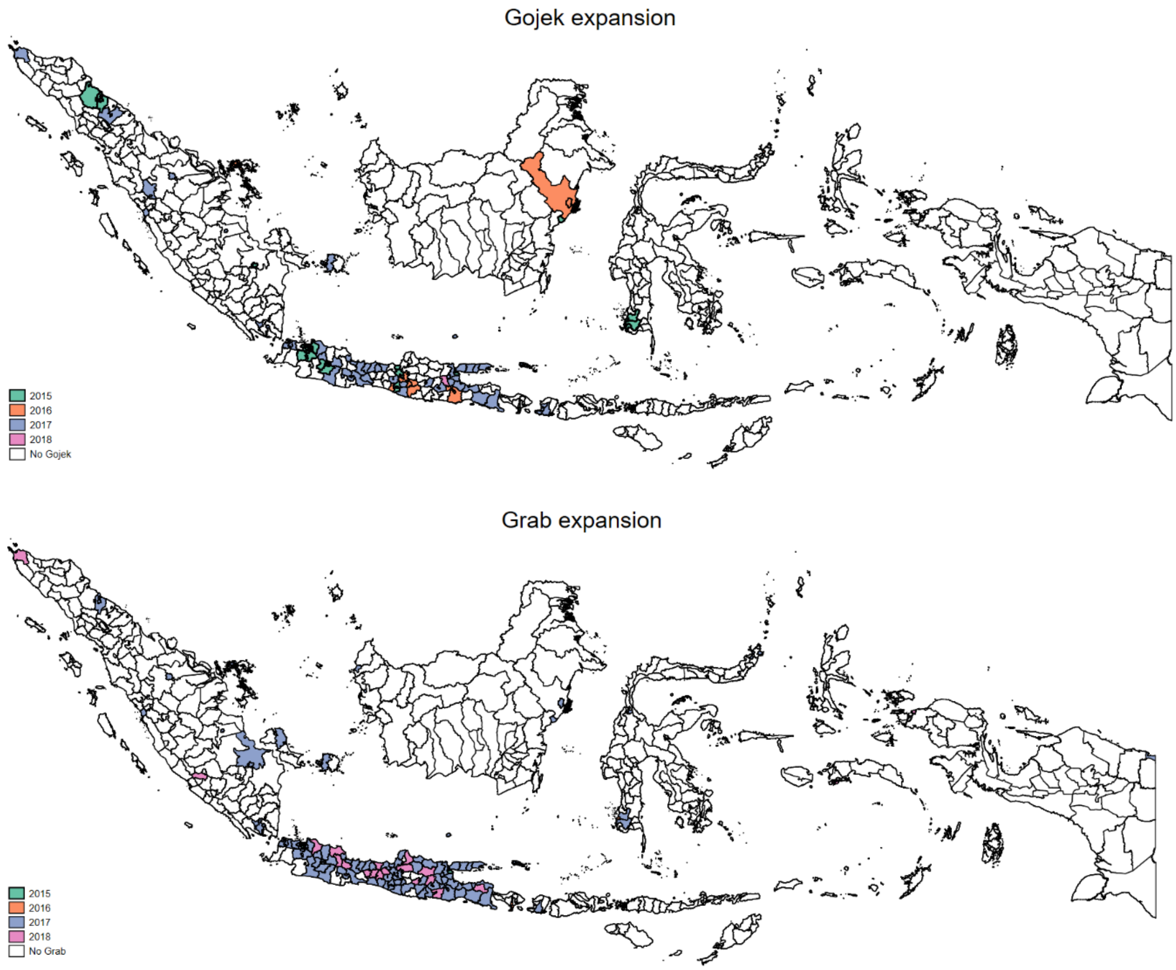
4.2 Stylized facts about food super-apps in Indonesia

Currently, there are two leading super app providers in Indonesia. The first is Gojek, an Indonesian company founded in October 2010, which initially operated as a call center service. The aim was to connect motorcycle riders with consumers, as they operated sporadically and spent long periods waiting for customers (Azzuhri et al., 2018). In January 2015, Gojek secured seed funding to develop a ridesharing application. By March 2018, it had expanded to Vietnam, Thailand, Singapore, and the Philippines, and in Indonesia reached 107 districts, including 50 cities and 57 regencies (see Fig. 4.1, Fig 4.2). Of these, only 10 districts were served exclusively by Gojek (Appendix C, Table C1).

The second company is Grab, a Malaysian app-based taxi-hailing company[8], which expanded its service in Indonesia in 2014 as a ridesharing, motorcycle-rice hailing, and delivery app. By the first quarter of 2018, Grab covered more than 148 districts (Figure 4.1), of which 63 are cities and 85 are regencies. Grab not only has more district coverage than Gojek, but it also covers more regencies (Figure 4.2). Of these, 51 districts were exclusively served by Grab, while 97 districts were served by both Gojek and Grab. As of March 2018, the remaining 339 districts were not served by either platform (Appendix C, Table C1).

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

Figure 4.1 Expansion of Gojek and Grab digital platforms in Indonesian districts during 2015-2018

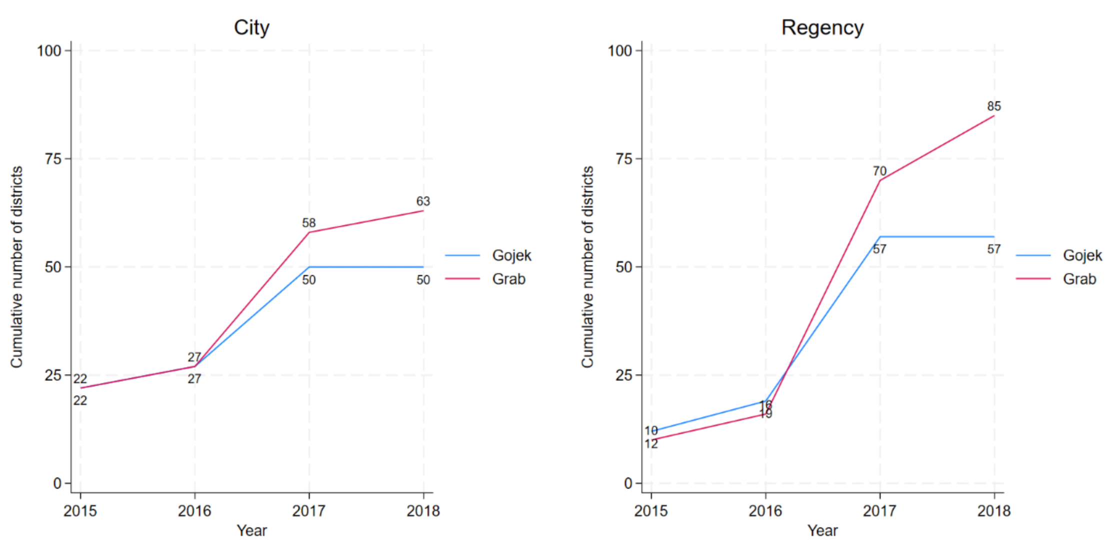


During the first few months after the launch of super apps, food-related services (i.e., pick-up, delivery, and transporting customers to restaurants) were the most in demand. Gojek and Grab responded by launching a food delivery feature that connected stores and consumers in several cities. Released in April 2015, this feature allowed consumers to order food online from vendors (i.e., restaurants, western fast food chains, local eateries, street food stalls) for delivery by motorbike riders. Through the app, consumers could view food properties such as portion size, ingredients, and price, thus simplifying the transaction process.

Gojek and Grab have changed the operational and marketing systems of the food industry. Small restaurants can open a joint operation from one spot, while individual kitchens can operate without physical locations, using home kitchens, pick-up lockers, and curbside parking lots (Ahuja et al., 2021, Meemken et al., 2022). Available food options include 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, dessert drinks, and ultra-processed foods (i.e., sausages, meatballs, nuggets, soft drinks). By late 2015, Gojek expanded its services to include partnerships with supermarkets and minimarkets, enabling users to order staple food, fruits, vegetables, and meat products online. Grab followed with a similar partnership in 2019.

Gojek and Grab have reported substantial contributions to Indonesia's economy, based on recent studies they funded. These include a 2.8 % increase in Indonesia's GDP[9] and the creation of job opportunities for 1.7 million people. In 2019, there were more than 150 million users and an average of 9.6 million rupiahs (more than US$676) in transactions per customer per annum[10], which helped buffer economic shocks during the COVID-19 pandemic (Walandouw & Primaldhi, 2021).

Figure 4.2 Expansion of Gojek and Grab digital platform services in cities and regencies



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

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

4.3 Materials and methods

4.3.1 Data

The datasets from Indonesia that we use in this study are listed below and described subsequently:

- Gojek and Grab app expansion from 2015 to 2018
- Basic Health Survey (*Riset Kesehatan Dasar* - Riskesdas) 2007, 2013, 2018
- National Socioeconomic Survey (*Survei Sosioekonomi Nasional* - Susenas) 2012-2018
- Village Potential Census (*Potensi Desa* - Podes) 2011
- District geolocation data 2021

Gojek and Grab expansion data contain the launch date information for each district served by the two digital platforms. We use the staggered adoption of their mobile applications rollout at the district level between 2015 and 2018 as the main explanatory variable. Gojek officially provided us with the launch date information for each district where they operate. For Grab, this information was gathered by tracking the news in local media outlets or social media.

Riset Kesehatan Dasar (Riskesdas) is a repeated cross-sectional health survey that collects information on nutritional status, unhealthy food consumption, and physical activity from over one million individuals. Riskesdas 2013 serves as the baseline, as this is the most recent available health survey conducted before the introduction of super apps in 2015. This dataset is ideal as a baseline, since the super apps had not yet launched and were unlikely to have affected the outcomes. Riskesdas 2018 serves as the endline, allowing sufficient time to observe long-term effects. We also use Riskesdas 2007 to assess pre-trends of outcomes. Riskesdas data are used in two ways: aggregated at the district level and the individual level. For the district-level analysis, individual outcomes are aggregated at the district level using residential district identifiers and merged with super-apps district adoption data to construct a panel of 497 districts. For the individual-level analysis, we link each individual's district of residence to the year of super apps adoption in that district.

Survei Sosioekonomi Nasional (Susenas) is a repeated cross-sectional survey conducted annually, providing information on household welfare and detailed food consumption from around 300,000 households. We use this data to investigate the effect of super apps’ expansion on food consumption. As Susenas are collected annually, we use data from 2012 to 2018 to track consumption trends and explore potential mechanisms. As with Riskesdas data, we also use Susenas data for aggregated district-level and individual-level analyses.

Potensi Desa (Podes) is a village census collecting information on the livelihood, geographical information, infrastructure, and socioeconomic network of each village in Indonesia. Village-level information from Podes 2011 is aggregated at the district level as baseline covariates in the regression, as this is the closest available data to the baseline period. Geolocation data is obtained from the *Badan Pusat Statistik* (Statistics Indonesia), containing districts' longitude and latitude data in 2021. This data is used to conduct a robustness check using spatial analysis.

4.3.2 Key variables

We define the treatment variable in two ways: (1) a binary indicator with the value of 1 if a district was served by (Gojek, Grab, or both) and 0 otherwise; and (2) the year in which a super app first entered the district. To ensure alignment with the other datasets used in this study, the adoption period is defined as between January 2015 and March 2018. Within this period, 158 districts out of the total 497 districts are classified as treatment districts. Later on, in the individual-level analysis, we consider individuals living in districts served by any of the super apps as the treatment group.

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

$$BMI = \frac{w}{h^2} \tag{4.1}$$

We determine an individual's nutritional status using the World Health Organization (WHO) standard: underweight (BMI < 18.50); overweight (BMI ≥25); obese (BMI≥30). We also provide an alternative classification using the Asian population cutoff (available in Appendix C), which is relevant given the higher risks of overweight and obesity at lower BMI levels in our sample (Tan, 2004). The cutoffs are: overweight (BMI≥23); obese (BMI≥27).

We acknowledge that BMI does not account for body fat and muscle mass composition, which may obscure the identification of overweight and obesity. To corroborate BMI results, we use waist circumference measurements taken one centimeter above the navel for individuals aged 15 and above. Central obesity is defined as a waist circumference above 84 cm for females and above 94 cm for males (World Health Organization, 2000, Obesity in Asia Collaboration, 2007). We also apply an Asian-specific cutoff, where central obesity is defined as a waist circumference above 80 cm for females and 90 cm for males.

We use physical activity and unhealthy food consumption measures from Riskesdas to explore impact pathways associated with super apps expansion (Brouwer et al., 2021). Physical activity is measured by the number of minutes individuals engaged in doing heavy (i.e., lifting heavy objects, doing sports) and medium (i.e., cooking, walking) activity in the past week. Individuals meeting at least 150 min of moderate and 60 min of heavy activity per week are classified as physically active (World Health Organization, 2020). Unhealthy food consumption is indicated by any intake of sugar-sweetened foods or drinks, fried or grilled foods, instant foods, and caffeinated drinks.

Additionally, we use Susenas data on household food expenditure, food quantity, and macronutrient intake (protein, fat, carbohydrate, and calories). Food items are grouped based on major categories, including a separate group for prepared food such as rice dishes, grilled meat, noodle dishes, and snacks. To calculate per capita consumption, we divide household-level indicators by the number of household members.

4.3.3 Identification strategies

4.3.3.1 District-level analysis

We analyze the impact of super apps on nutritional outcomes by comparing treatment and control districts, before and after their adoption. The analysis does not distinguish between companies, as the aim is to examine the overall impact of super apps. This approach assumes similar trends in outcomes between treatment and control districts prior to the 2015 rollout, allowing post-adoption differences to be attributed to the treatment. To validate this parallel trend assumption, a placebo regression is performed by using outcome data from the pre-rollout period (2007 and 2013).

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

$$N_{d,t} = \beta_1 Tr_{dt} + \gamma_t + \alpha_d + \varepsilon_{dt} \tag{4.2}$$

In Eq. (4.2), 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 using population weight available in the datasets. β_1 captures the effect of digital platforms' presence on district-level outcomes. Tr_{dt} equals 1 for districts with super apps between January 2015 and March 2018, and 0 otherwise. γ_t and α_d are year and district fixed effects. ε_{idt} is the error term. We also conduct heterogeneous treatment effect analyses based on district characteristics, such as city/regency status, GDP level, development indicators, and available service types (e.g., general and food delivery).

As digital platform entry may correlate with factors affecting consumption and nutrition trends, this poses a threat to our identification strategy. To address this, we implement a doubly robust estimator by combining inverse probability weighting (IPW) and outcome regression to balance characteristics between treatment and control groups (Sant'Anna and Zhao, 2020). The IPW approach generates weights based on the inverse probability of super app entry into a district conditional on factors linked to platform expansion, such as population size, welfare status, education level, and other socioeconomic variables (Berger et al., 2018, Hall et al., 2018). Outcome regression models the relationship between the outcome and treatment, adjusting for baseline covariates to create a counterfactual outcome. The covariates capture both the determinants of super app entry and pre-treatment trends in nutritional outcomes. Using IPW and outcome regression models mitigates bias from misspecification in either model and improves the validity of our estimates.

We also account for potential spatial spillover, acknowledging that digital sector employment allows for commuting and services extension into nearby districts depending on infrastructure (Siregar, 2022). We test for spillovers by identifying control districts located within 25 and 50 km, as these distances match the companies' operational service limits[11]. These districts are either included as treated (to account for potential exposure) or excluded from the analysis (to construct a cleaner control group). This approach allows us to assess the sensitivity of our estimates to geographic contamination.

[11] https://www.indonesiana.id/read/126196/monopoli-jarak-ojek-online-merugikan-penumpang

4.3.3.2 Individual-level analysis

We also conduct individual-level analyses using a repeated cross-section estimator to assess the distributional effects of super apps and their heterogeneous impacts across population subgroups. The following individual-level regression model is used:

$$N_{i,d,t} = \beta_1 Tr_{dt} + \gamma_t + \alpha_d + \varepsilon_{idt} \quad (4.3)$$

where the *i* denotes the outcome at the individual level. ε_{idt} is the error term clustered at the district level. Since the treatment is assigned at the district level and there is no information on individual usage of the apps, our estimation measures the intent-to-treat effects. The model includes the same controls in the district-level regressions, with additional individual-level covariates, such as education level, socioeconomic status, gender, age, and employment. We conduct heterogeneous treatment effect analyses across subgroups defined by welfare level, gender, age group, and education level.

$$\widehat{RIF}\ (N_{i,d,t}; \hat{q}_\tau) = \beta_\tau Tr_{dt} + \gamma_t + \alpha_d + \varepsilon_{idt} \quad (4.4)$$

While Eq. (4.3) captures the average effect of super apps, we also estimate their impact across the BMI distribution using a Recentered Influence Function (RIF) regression within a difference-in-differences model, as specified in Eq. (4.4) (Firpo et al., 2009, Rios-Avila, 2020). Specifically, we construct the RIF at selected percentiles of BMI (e.g., 5th, 10th, 15th… 95th) to estimate the treatment effect (β_τ) across the distribution. This approach assumes that RIF-transformed BMI in treated and control districts would have followed similar trends across all distribution points in the absence of treatment. To address potential selection bias in digital platform expansion, we apply inverse probability weighting (IPW) based on baseline district characteristics. We also control for district fixed effects (α_d) to account for unobserved time-invariant factors (i.e., geographic location, culture) and year fixed effects (γ_t) to account for common time shocks (e.g., national policies, price shocks).

4.3.3.3 Impact pathways

To investigate the impact pathways of super apps on nutritional outcomes, we examine several dimensions of the food environment, such as physical activity, unhealthy food consumption, food expenditure, and macronutrient intake. The analysis for physical activity and unhealthy food consumption using Riskesdas follows the model specified in Eq. (4.2). Since expenditure and food consumption data in Susenas are available annually, we conduct a multiple-period analysis (2012-2018) using a staggered difference-in-differences model as specified in Eq. (4.5). This is done by estimating a weighted average of all possible 2x2 difference-in-differences combinations across different periods in our samples (Callaway and Sant'Anna, 2021). The following staggered difference-in-differences model is used:

$$E_{d,t} = \sum_{k=t}^{T} \beta_k \, Tr_{d,t} + \gamma_t + \alpha_d + \varepsilon_{d,t} \tag{4.5}$$

Where $E_{d,t}$ represents expenditure and food consumption indicators. Parameter β_k captures the average treatment effect across different periods. Using Susenas, we observe a 5-year pre-trend by comparing districts where super apps entered in 2018 using data from 2012 and 2013. Conversely, for districts where super apps were launched in 2015, we observe up to three years of post-treatment data (e.g., comparing 2014 and 2018). In each case, treated districts are compared to control districts, defined as those never treated by March 2018.

4.4 Results

4.4.1 Descriptive statistics

The descriptive statistics confirm the double burden of malnutrition hypothesis, where the rate of overweight/obesity increases outpaces underweight reduction (World Health Organization, 2016, Popkin et al., 2020). Between 2013 and 2018, the proportion of overweight adults increased from 27 % to 35 % in control districts and from 31 % to 40 % in treated districts (WHO cutoff, Table C2 in Appendix C). Obesity rates increase from 6 % to 9 % in control districts and from 7 % to 12 % in treated districts. The patterns are similar when using the Asian cutoffs. Meanwhile, underweight rates slightly decreased by around 11 % in both groups within the same period.

Waist circumference is also used to provide a more comprehensive assessment of obesity. Central obesity rates increased by 26-27 % (WHO cutoff) and 17-18 % (Asian cutoff) in both control and treated districts between 2013 and 2018. These findings confirm the BMI-based categorization of overweight and obesity. At the district level, overweight and central obesity are strongly correlated, with coefficients of 80.67 % (WHO cutoffs) and 75.92 % (Asian cutoffs), suggesting that BMI remains a reliable proxy to determine nutritional status in the Indonesian context.

Districts with super apps have higher overweight/obesity incidence and stronger economic indicators (i.e., urbanization, education attainment, access to amenities) than control districts (see

Table C2). Furthermore, individuals in treated districts are more likely to live in urban areas, have above junior high education, and be employed. This suggests systematic differences between treatment and control groups, meaning that outcomes cannot be directly compared. We formally address this issue using strategies detailed in Eq. (4.2).

4.4.2 Determinants of super apps entry

Understanding the factors correlated with Gojek and Grab's entry decision is important to address potential endogeneity issues, as these factors may also affect nutritional outcomes. Table 4.1 shows factors associated with super app entry included as covariates in the main estimation. Super apps' entry is strongly predicted by urban population size, median working age, education, and being in the Java and Bali islands (see Table 4.1). Gojek's expansion is additionally influenced by industrial employment, internet access, and population growth. While some of these findings align with patterns in developed countries (Berger et al., 2018, Hall et al., 2018), factors such as urbanization, education, employment, and age are also important in Indonesia. These results reflect differences in business models where super apps in LMICs expand not only in populous areas but also in areas with a growing economy. To address the endogeneity issue, these factors are incorporated in the main estimation using a doubly robust estimator.

Table 4.1 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 Java 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. All the independent variables are measured in standard deviation to allow for magnitude comparison. Column (1) compares characteristics of districts with Gojek and control districts. Column (2) compares characteristics of districts with Grab and control districts. Column (3) compares characteristics of districts with either platform and control districts. Data on population, education, age, employment, ownership of phones, internet, vehicles, and regional gas prices was collected from Susenas 2012. Distance to the provincial 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, minimarkets, traditional markets, and restaurants in the district. The trend in population calculates the relative annual growth of the district population from 2012 to 2014.

4.4.3 District-level findings

4.4.3.1 Placebo tests

Before going to the main estimation, we test for pre-treatment differences using the model in Eq. (4.2). We merge district-aggregated Riskesdas 2007 and 2013 data with super-apps expansion data to compare outcomes between districts that eventually have super apps and those that do not. Figure 4.3 shows no significant difference for most outcomes during the pre-treatment period, except for overweight incidence, which is lower in treated districts. We address this issue by including covariates to ensure conditional parallel trends (Figure 4.3, green tick marks). No pre-trend differences are found for BMI, waist circumference, and obesity or underweight incidences.

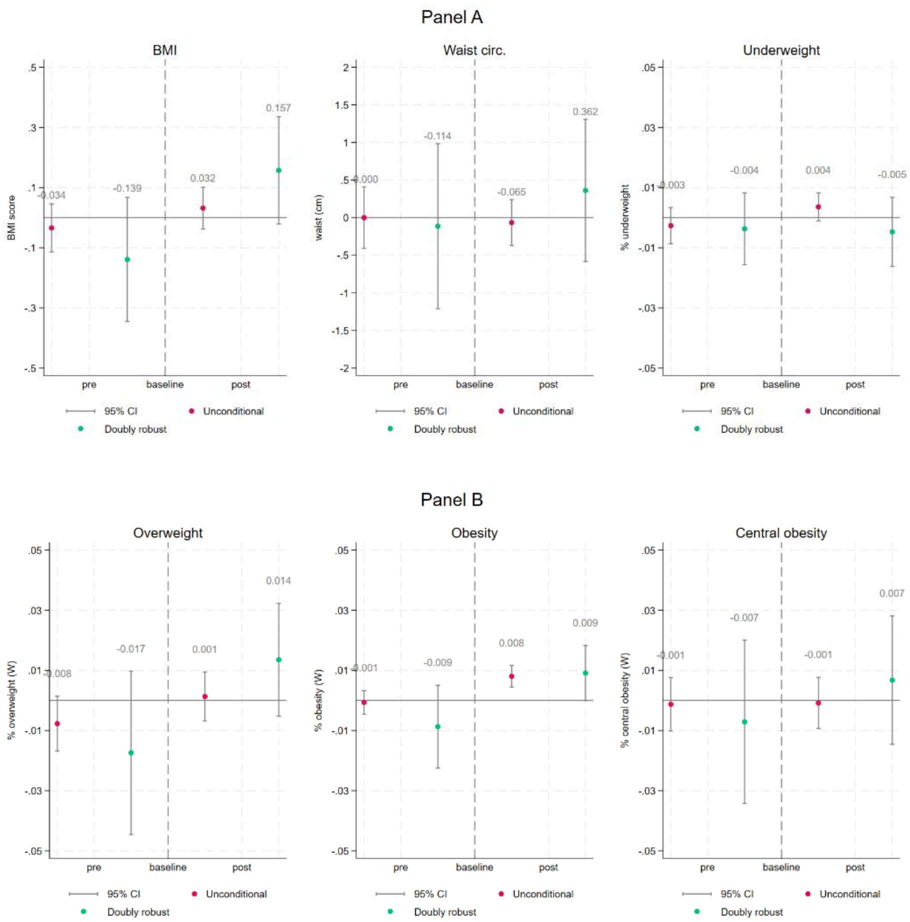
To account for potential confounding factors, we incorporate baseline covariates that predict super-apps entry and capture trends in nutritional outcomes among control districts, ensuring conditional parallel trends. These covariates include the proportion of urban residents, those with above junior high education, the employment rate, and the median working age. Additional district-level factors potentially affecting obesity are also included, such as GDP, availability of community health centers and hospitals, access to clean water and toilets, gender ratio, and health insurance (Rachmi et al., 2017).

4.4.3.2 Main results

This sub-section focuses on the effect of super apps on nutritional outcomes at the district level using the model in Eq. (4.2) with district-aggregated Riskesdas 2013 and 2018 data. Before incorporating covariates, districts with super apps have a higher obesity incidence by 0.8 p.p. using the WHO cutoff than districts without super apps (Figure 4.3, Panel B, red tick marks). After adjustment, super apps significantly increased BMI by 0.16 (Figure 4.3, Panel A) and obesity and overweight incidences by 0.9-1.4 p.p. (Figure 4.3, Panel B). These results are more robust and larger in magnitude than from unconditional estimators, suggesting that omitting baseline covariates would underestimate the impact of super apps. Therefore, we refer to the doubly robust estimation results in the following discussion.

We find that super apps have no significant impact on nutritional outcomes when using the Asian cutoff, which applies a lower threshold for overweight and obesity than the WHO cutoff (Appendix C, Table C3). This finding indicates that the effects of super apps are more pronounced among individuals with higher BMI, as classified by WHO criteria. We also find no significant effect on waist circumference and central obesity incidence (Figure 4.3, Panels A and B). However, the direction is consistent with our findings on BMI and obesity, lending some suggestive evidence to support our main estimations.

Figure 4.3 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, while pre-treatment period compared Riskesdas 2007 and 2013 data. Estimated using the 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.

4.4.3.3 Heterogeneous effects by district characteristics

Table 4.2 shows that BMI and overweight/obesity incidence are significantly higher in cities. Cities with super apps have a 0.6 higher BMI and a 1.8 cm larger waist circumference than those without super apps. This is followed by increases in overweight, obesity, and central obesity incidences (WHO cutoff) by around 2.2 p.p. - 4.2 p.p., which account for more than 10 % relative increases from the baseline period. In these cities, the incidence of adult underweight is also significantly lower. These findings are consistent when using the Asian cutoff (Appendix C, Table C3). As the pre-trends of outcomes are statistically significantly different from zero, these findings should be interpreted as suggestive rather than definitive evidence (Appendix C, Table C4).

We also find consistent evidence using other district characteristics. BMI and obesity incidences are higher in districts with above-median GDP, aligned with our findings on urban effects. The findings remain after excluding metropolitan and early-adopters districts, with up to 1 p.p. increase in obesity incidence among late-entry and non-metropolitan districts. This finding indicates that, despite the smaller effect, super apps still contribute to weight gain in less affluent areas.

Lastly, we test whether the impact of super apps is driven by their online food delivery feature. This comparison focuses on districts where, by 2018, individuals could order food directly via the app for delivery by motorbike riders. Table 4.2 shows that without the food delivery feature, super apps' effect on BMI and overweight disappear, except for obesity incidence. While these findings suggest that super apps' effect is driven by food delivery, the statistically significant pre-trends warrant caution in interpretation (Appendix C, Table C4).

Table 4.2 Heterogeneous treatment effects of super apps on BMI, waist circumference, and nutritional status

Heterogeneity	**N (T; C)**	**BMI**	**Waist circum ference**	**Over weight**	**Obesity**	**Central obesity**	**Under weight**
All sample	T: 158	0.157*	0.362	0.014	0.009*	0.007	-0.005
	C: 339	(0.091)	(0.483)	(0.01)	(0.005)	(0.011)	(0.006)
Cities	T: 65	0.596***	1.8***	0.042***	0.022***	0.032**	-0.032***
	C: 33	(0.182)	(0.652)	(0.016)	(0.008)	(0.013)	(0.012)
Regencies	T: 93	0.103	-0.048	0.005	0.007	-0.005	-0.006
	C: 306	(0.067)	(0.351)	(0.012)	(0.004)	(0.016)	(0.007)
GDP above median	T: 136	0.177*	0.52	0.012	0.009**	0.008	-0.009
	C: 113	(0.092)	(0.429)	(0.01)	(0.004)	(0.01)	(0.006)
GDP below median	T: 22	0.05	-1.08*	0.019	0.008	-0.01	0.013
	C: 226	(0.138)	(0.648)	(0.019)	(0.009)	(0.02)	(0.013)
With food delivery	T: 41	0.569***	3.209***	0.046**	0.021**	0.061**	-0.027***
	C: 339	(0.195)	(01.04)	(0.021)	(0.009)	(0.026)	(0.008)
Without food delivery	T: 117	0.096	-0.104	0.01	0.008*	-0.001	-0.001
	C: 339	(0.069)	(0.342)	(0.009)	(0.005)	(0.01)	(0.006)
Excl. metropolitan	T: 155	0.146	0.283	0.013	0.009*	0.005	-0.004
	C: 339	(0.09)	(0.446)	(0.01)	(0.005)	(0.011)	(0.006)
Excl. early adopters	T: 137	0.116	0.109	0.01	0.008*	0.002	-0.003
	C: 339	(0.08)	(0.387)	(0.009)	(0.004)	(0.011)	(0.006)

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 WHO cutoff. Estimated using the 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. N is number of districts, T is treatment districts, and C is control districts.

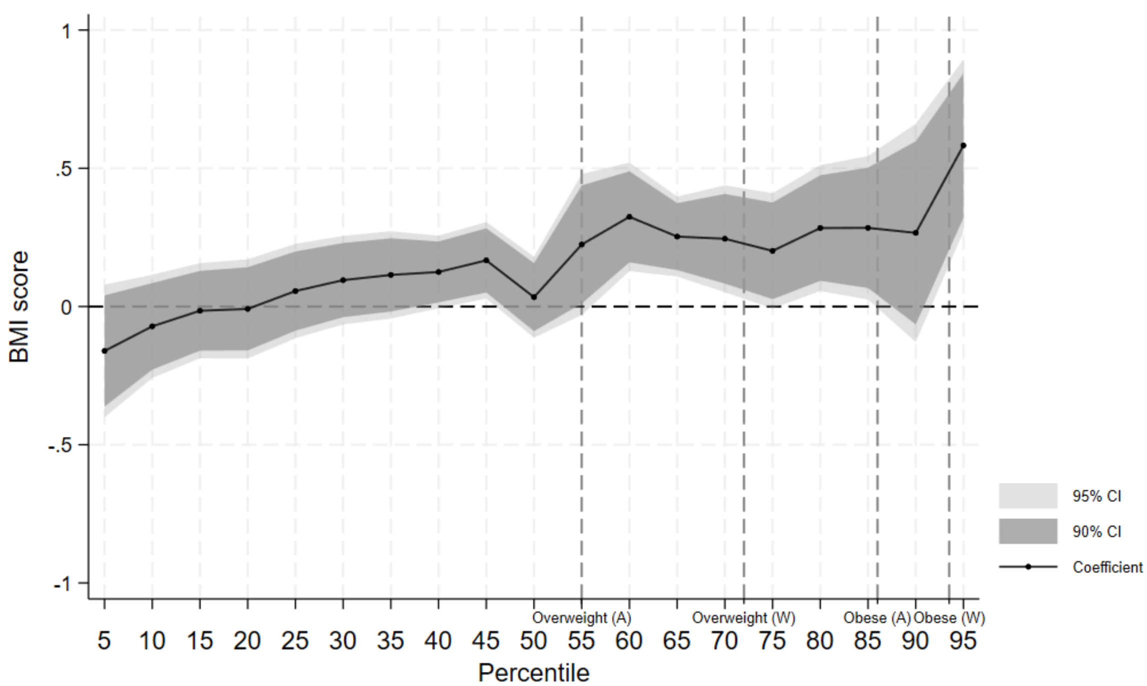
4.4.3.4 Robustness tests

We expect that the presence of spillover will underestimate our estimations. We find mild spillover effects among control districts located within 25 km of treated districts: including them does not significantly change our estimation with a 0.19 BMI and 0.9 p.p. obesity increase, while excluding them slightly increases these effects (Appendix C, Table C5). The parallel trend assumption also holds in both cases, suggesting that treatment and control districts remain comparable. Excluding districts within 50 km results in larger estimates but violates parallel trends, indicating that the remaining control group may not serve as a valid counterfactual anymore. These findings suggest that spillovers are still present within 50 km, but overly restrictive exclusions can compromise identification.

4.4.4 Individual-level findings

Individual-level analysis utilizes the model in Eq. (4.3) and (4.4). District-level aggregated analysis shows that super apps have a greater impact on obesity than on overweight incidence, indicating stronger effects in the upper BMI distribution. To test this hypothesis further, an RIF-regression analysis using the model specified in Eq. (4.4) is performed. Figure 4.4 illustrates the results. The analysis shows that super apps tend to increase BMI among overweight and obese individuals (Asian and WHO cutoffs), with a more pronounced effect starting at the 40th percentile and above. Pre-trend tests using Riskesdas 2007 and 2013 hold across the BMI distribution, supporting the robustness of the RIF-regression estimates (Appendix C, Fig. C1).

Figure 4.4 The effects of super apps across BMI distribution



Note: Coefficients with 95 % and 90 % confidence intervals are shown. RIF-regression of individual-level data, estimated using the inverse probability weighting (IPW) method. Riskesdas 2013 and 2018 are used for this analysis. The overweight and obesity cutoff was determined using the Asian (A) and the 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 Java and Bali. Additionally, individual-level variables such as sex, age, education, employment, and socioeconomic status are incorporated.

Individual-level data allow us to conduct a heterogeneous treatment effects analysis using individual characteristics. We conduct repeated cross-section difference-in-differences using the doubly robust estimator as specified in Eq. (4.3). The sample was divided based on gender (male vs. female), per capita income level (below and above the median), education level (below and above junior high school), employment status, and age group. We find that super apps are associated with increased BMI and overweight/obesity incidences among those in higher-income groups, higher-education groups, employed, and aged 19-29 (Table C6 in Appendix C). These findings confirm the market segmentation of super apps among more affluent individuals, which might explain their greater effects in these sub-groups.

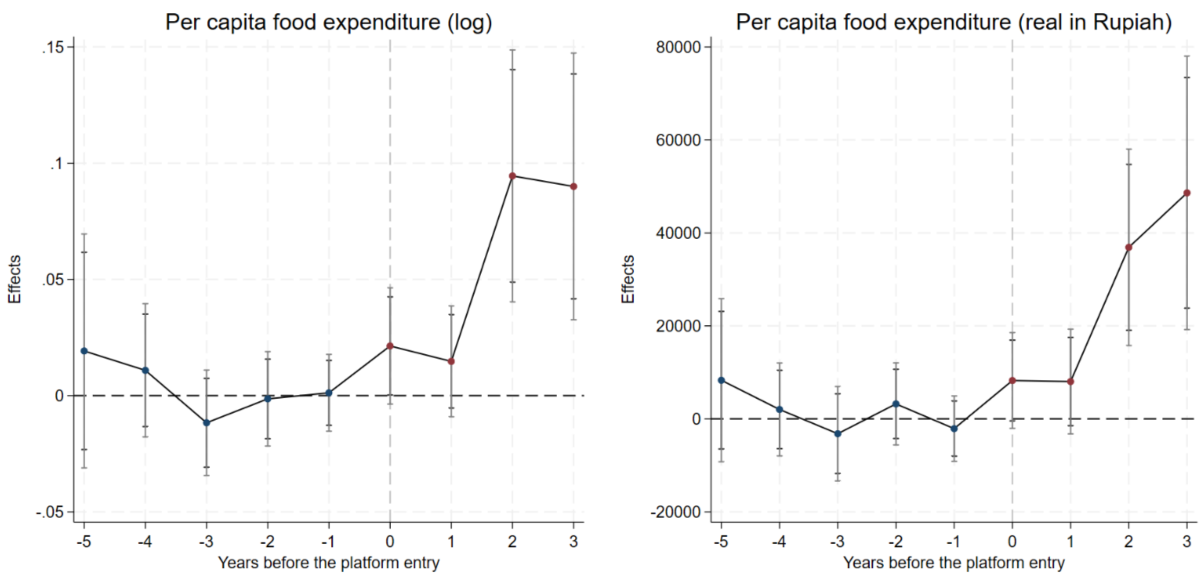
4.4.5 Impact pathways

Overweight and obesity among adults likely happen when energy consumption exceeds energy spent, due to higher food intake or insufficient physical activity, both of which may be affected by super app usage. In this section, we combine super apps expansion data with physical activity and unhealthy food consumption from the Riskesdas data and detailed food consumption from Susenas to examine their relationships.

We use the model in Eq. (4.2) to estimate the super-apps' effect on physical activity and unhealthy food consumption. The findings indicate no significant effect on the amount of heavy and moderate physical activity at the district level (Table C7 in Appendix C). On the other hand, weekly consumption of salty foods in treated districts significantly increased by 3.5 p.p. compared to the control district (Table C7 in Appendix C).

While super apps do not significantly affect physical activity, they may induce changes in food consumption. We corroborate this by estimating Eq. (4.5) using Susenas, which provides more granular insights into household consumption. We compare treatment and control districts across multiple years, confirming parallel pre-trends in per capita food expenditure prior to the super app launch. After the first year of the platforms' operation (t1), food expenditure (in log and real terms) starts to increase and continues to grow as their coverage expands. In districts with super apps operating for more than two years, per capita food expenditure increases by up to 9 %, which is approximately Rp 48,600 (US$3.42) per week (Figure 4.5).

Figure 4.5 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 the staggered difference-in-differences 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 food expenditure and consumption between 2012 and 2018. The findings show that super apps are associated with increased total and food expenditures, as well as calorie and fat intake (Table 4.3). Per capita total expenditure increases by around Rp 72,117 (US$5.08) per week (8.4 % relative increase[12]), indicating improved welfare in treated districts.

Food expenditure in treatment districts rose by around Rp 25,447 (US$1.79) per capita (6.3 % relative increase). Super apps also increase macronutrient consumption, with increases of 1.5 % in calories, 2.5 % in protein, 4 % in fat, and 1.7 % in carbohydrate relative to the mean. At the food group level, we find significant relative increases in expenditure on fruit (19.4 %), meat (10.5 %), and prepared food (9.4 %) in treatment districts (Appendix C, Table C8). The increase in prepared food consumption is expected, as most food products offered on the platform are categorized as

[12] The relative effect is calculated by dividing the estimated regression coefficient by the mean of the outcome variable.

unhealthy. However, the increases in fruit and meat expenditure suggest that super apps may also support healthier dietary patterns.

Table 4.3 The effects of super apps on weekly food expenditure and macronutrients

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	

Notes: *** p<0.01, ** p<0.05, * p<0.10. ǂ calculated for per capita in households. Estimates are calculated using doubly robust difference-in-differences methods. Variables are aggregated at the district level from the Susenas 2012- 2018 datasets. 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

A heterogeneous treatment effect analysis using household expenditure quantiles reveals differences in consumption patterns across socioeconomic levels. Super apps increase total household expenditure in the highest expenditure quantile (5^{th}), while food expenditure and fat consumption increase significantly in the third quantile (Appendix C, Table C9). Fruit expenditure increases among households in the second to fifth quantiles. Among those in the lowest expenditure quantile (1^{st}), cigarette expenditure increases, while among those in the fifth quantile, sugar and cigarette expenditure decrease. These unequal effects across the distribution raise concerns, as the benefits of super apps appear concentrated among higher-income households.

4.5 Discussion

The findings of this study reveal four key points. First, super apps contribute to increased BMI and obesity incidence. Second, these effects are more pronounced among younger individuals with higher education or income, and those who are employed, as well as those who are already overweight/obese. Third, super apps increase unhealthy and prepared food consumption, potentially explaining the observed increase in BMI and obesity. Fourth, super apps may have potential benefits, such as reducing underweight and increasing meat and fruit consumption.

Our findings of adverse effects of super apps on nutritional transition are consistent with previous studies examining individual risk factors in food delivery usage (Dana et al., 2021, Dominici et al., 2021, Keeble et al., 2021, Keeble et al., 2022). While earlier studies focused on individual-level experiences, our study adds to the literature by showing that these effects are sufficiently systemic and large to be detectable at the aggregated district level. The availability of super apps contributes to a 10 % relative increase in overweight and obesity over time, with higher effects in cities than in regencies and higher than in lower-GDP districts. Enabling factors include earlier entry to cities, more diverse food availability, and better road infrastructure and internet connectivity (Hall et al., 2018).

Results from individual-level analysis confirm the district-level effects: super apps disproportionally affect younger adults (19-29 years), higher-income groups, and urban residents. These groups are the most active platform users due to greater preference for convenience and more time constraints to acquire or prepare food (Maimaiti et al., 2018, Meemken et al., 2022, Safira and Chikaraishi, 2022). High work demands and prolonged internet use may further drive greater consumption of calorie-dense prepared foods and sedentary behaviors (Poobalan and Aucott, 2016, Michelle et al., 2024). Consistent with evidence that shows platform users often have higher body weight (Dana et al., 2021, Dominici et al., 2021), we find that BMI impacts are larger among those already overweight or obese. The findings among productive-age and vulnerable populations are concerning, as they may accelerate the onset and severity of obesity-related chronic diseases in later life. Our findings highlight the role of digital platforms in shaping human capital development in LMICs.

This study finds that consumption of salty and prepared foods likely mediates the rise in BMI and overweight/obesity incidence, consistent with previous studies showing an excess supply of unhealthy foods (high in energy, fat, sodium, and sugar) on digital platforms (Granheim et al., 2022, Horta et al., 2022, Meemken et al., 2022, Bennett et al., 2024). While other studies link super apps to sedentary lifestyles (Brouwer et al., 2021), we find no strong evidence for this. It is possible that super apps reduce physical activity related to food preparation and cooking, but our indicators do not differentiate activity types, offering an avenue for future research.

Beyond food, we find that super apps are linked to increased cigarette consumption among the poorest households. A plausible explanation is that low-income households may represent gig-workers who are working long and demanding hours, increasing their risk for smoking (Yuan et al., 2022). In contrast, we find that higher-income households showed decreased cigarette consumption. This finding is concerning, as it suggests that super apps may reinforce socioeconomic disparities in smoking behavior.

Our findings also suggest potential benefits of super apps, including decreased underweight incidence in cities and increased total expenditure, food expenditure, macronutrient intake, and expenditures on meat and fruit. These results are consistent with current evidence that improved internet access can enhance household food security through increased access to information and income (Ankrah Twumasi et al., 2021, Ardianti et al., 2023). Our study extends this discussion by showing that the benefits extend beyond monetary gains and include improved dietary diversity. However, these benefits are more pronounced among higher-welfare households, likely due to perceived risks of inferior fresh produce and reluctance to pay extra service fees among lower-income groups (Bennett et al., 2024). At the same time, super apps may enable access to unhealthy, cheaper foods in deprived areas, potentially worsening nutritional inequality.

This study contributes to the emerging literature on the impact of digital platforms on nutrition and has significant public policy implications. Super apps currently operate with minimal government oversight. However, regulatory measures, such as nutrition labelling, health branding, and restrictions on pricing strategies and advertisement of junk food, could help mitigate negative health effects (Brouwer et al., 2021, Bennett et al., 2024). The global surge in digital platforms usage since the COVID-19 pandemic, especially among younger adults, highlights the need to prioritize this group (Michelle et al., 2024, Meemken et al., 2022). At the same time, initiatives such as linking super apps with traditional markets, supermarkets, and farmers (Shen et al., 2023, Liu et al., 2024) and providing ready-to-cook meal packages could improve access to diverse diets and convenience, while sustaining business growth.

4.6 Conclusion

This study examines the impact of super apps providing food delivery, ridesharing, and other daily services on nutritional status and food consumption. Our identification strategy utilizes district-level expansion of Gojek and Grab, the two largest super apps in Indonesia, between 2015 and 2018. We find that super apps have adverse effect on nutritional transition, by increasing BMI and obesity incidence. These effects are mediated by increased consumption of unhealthy and prepared food. On the other hand, super apps improve under nutrition and dietary diversity, highlighting their potential to mitigate and reverse some negative nutrition trends, given the right policy approach.

5 Discussion, policy recommendations, and future research

5.1 Discussion

The three essays in this dissertation contribute to the understanding of underexplored and emerging risk factors of malnutrition in LMICs. Together, the three essays improve our understanding of the nutrition transition dynamics in LMICs through a comprehensive framework that examines individual, household, and environmental factors. There are three major conclusions from this dissertation. First, this dissertation confirms the complex interplay in malnutrition risk, where early-life deprivation increases future health risks, compounded by intra-household gender bias and exposure to the modern food environment, leading to undesirable nutrition outcomes in LMICs. Second, the negative effect tends to be more pronounced among vulnerable groups, including individuals with lower income or education, women, children, young adults, some ethnic minorities, and individuals with poor health. Lastly, the mechanisms that can explain this finding include lack of access to healthy and quality diets, lack of awareness of a healthy lifestyle, and sociocultural constraints.

The first essay estimates the impact of macroeconomic crisis on short- and long-term nutritional outcomes. To construct the crisis indicator, this study used the plausibly exogenous regional rice price inflation during the Asian Financial Crisis in the late 1990s in Indonesia. Using the combination of rice prices information and anthropometric data, this study estimates the impact of the crisis on children's nutritional outcomes, controlling for robust covariates. Furthermore, to test if the crisis has a long-term impact on health outcomes, an additional analysis was conducted by regressing childhood exposure to crisis on adult height and BMI.

This essay finds that rice price inflation led to a 0.16-point decrease in HAZ and a 4 percentage-point increase in child stunting, with the impact being larger when using rice prices in real terms. While this finding aligns with previous studies (Akresh et al., 2011, Yamauchi & Larson, 2019), this study contributes to the understanding of the macroeconomic crisis profile by highlighting its over-proportional negative impact on urban areas, boys, and those whose mothers have lower levels of education. These findings contribute to the literature on crisis mitigation by highlighting distinct profiles of macroeconomic crises, the population groups most vulnerable to them, and the protective factors that buffer their impacts. Beyond the immediate impacts, this essay also shows that the macroeconomic crisis increases the risk of obesity in the long run, potentially contributing to the current nutrition transition trajectory in Indonesia.

The second essay aims to understand micro-level dynamics that might play a role in determining an individual's nutritional outcomes by looking into the effect of ethnic-based marriage customs. This paper relies on the conceptual framework of asset transfers at the time of marriage, which hypothesizes that parents' decisions to marry off their children depend on the potential assets and human capital brought by their spouses. Parents are involved in this decision, as this affects their long-term economic and social consequences through co-residence or asset transfers between families. Information on ethnicity-based marriage customs, such as whether an individual belongs to an ethnicity that practices patrilocality, matrilocality, or bridewealth, is linked to the body mass index (BMI) of men and women.

This study finds that patrilocality is associated with increased male BMI and decreased female BMI, indicating discrimination against women. This finding is consistent with previous studies that show patriarchal practices having a negative impact on women's well-being (Allendorf, 2013, Bargain et al., 2022, Bau, 2021, Briones et al., 2018, Collins et al., 2022, Dasgupta, 2016, Harris-Fry et al., 2017, Rammohan & Johar, 2009, Sear & Mace, 2008). On the other hand, matrilocality and bridewealth likely have a protective effect on women's nutrition. The positive association between marriage customs and BMI is largest for those who are overweight, while the negative association between patrilocality and female BMI is largest for underweight women, highlighting the polarizing effects of marriage customs on nutrition. These findings highlight the role of sociocultural dynamics driving gender differences in overweight and obesity, which is one of the significant research gaps in designing effective malnutrition prevention policies (Ford et al., 2017).

The last essay moves on from socioeconomic and behavioral factors to the environmental aspects. Using the staggered rollout of the two largest digital platforms in Indonesia, called super apps, this study examines the impact of the changes in the food environment on the nutrition transition. In doing so, the estimation relies on a staggered difference-in-differences model by comparing districts and individuals with exposure to super apps before and after the first launch in 2015. To ensure that the treated and control groups have similar characteristics, this study uses a doubly robust estimator that incorporates covariates that both predict super apps entry and the trend in nutritional outcomes at the district level.

This essay shows that the expansion of these digital platforms, called super apps, increases BMI, which contributes to increases in overweight and obesity rates. The increase in BMI and overweight/obesity rates is higher in cities and districts with online food delivery features, and among those younger and more affluent (i.e., those with higher education, higher income, and employment). The BMI effects are also larger among individuals who are already overweight/obese. While the findings are consistent with similar studies conducted in higher-income countries (Dana et al., 2021, Dominici et al., 2021, Keeble et al., 2021, 2022), they also contribute to the emerging literature on modern food environments in LMICs. This study also shows that the observed increase in overweight and obesity rates is driven by increased unhealthy food consumption (i.e., salty and prepared foods). At the same time, exposure to super apps is linked with reduced underweight and increased meat and fruit consumption, highlighting the dual role of digital transformation on nutrition in LMICs.

5.2 Policy recommendations

Beyond its contribution to addressing data and research gaps on the nutrition transition topics in LMICs, this dissertation also makes significant contributions to improving nutrition policy design and implementation. The policy implications of the findings in each essay are explained below.

When improvement is most beneficial

This dissertation demonstrates that early-life nutrition plays a crucial role in shaping long-term health outcomes. The findings highlight the urgency of addressing malnutrition as early as possible, particularly during periods of crisis when household resources are scarce. Evidence from previous studies shows that interventions such as food assistance, public transfers, and remittances can buffer the short-term impacts of shocks (Block et al., 2004, Giles & Satriawan, 2015, Yamauchi & Larson, 2019). However, as shown in Essay 1, child growth outcomes often remain adversely affected despite the presence of social protection programs, suggesting inefficiencies or targeting gaps (Yamauchi & Larson, 2019). These results imply that crisis mitigation efforts must not only ensure program coverage but also improve the precision and monitoring of child well-being outcomes.

Equally important are health promotion and prevention programs during adolescence and adulthood, which can reduce the likelihood that high-risk groups develop non-communicable diseases later in life (Essay 1 and Essay 2). These may include nutrition-specific interventions across different stages of life, such as food assistance for pregnant women or iron and folic acid supplementation for school-aged girls. Furthermore, the long-term impact of early-life crises on obesity (Essay 1) underscores the need to systematically collect information on experiences of crisis, famine, or hunger within clinical settings, since individuals exposed to such conditions have a higher probability of developing metabolic diseases later in life (Cui et al., 2020, Kim et al., 2017).

Where improvement is most beneficial

This dissertation shows that nutrition policies need to take into account the regional context. Essay 1 demonstrates that macroeconomic and financial crises tend to have more pronounced negative effects on urban households, unlike famines or crop failures, which disproportionately affect rural households. This is likely because rural households may produce their own food and are more self-sufficient during food price crises (Headey et al., 2020). Therefore, policies aiming to stabilize staple food prices for urban and non-producer households during food-price spikes would likely be protective for children's long-term well-being (Yamauchi & Larson, 2019).

As shown in Essay 3, the high market dependence in urban areas also means that these populations are more affected by changes in the modern food environment. For population groups already vulnerable to malnutrition, it is therefore important to ensure transparency and promote health within the food industry. Nutritional labeling and marketing or advertising limitations should be encouraged or mandated in both the physical and digital worlds (Andreyeva et al., 2011, Bennett et al., 2024, Brouwer et al., 2021). Lastly, it is important to work with the private sector to foster innovations that align business growth with public health indicators. Efforts that leverage digital tools, such as connecting consumers with traditional markets or local farmers via super apps, can help ensure access to more diverse and healthy diets (Shen et al., 2023, Liu et al., 2024).

Who benefits most from improvement

This dissertation highlights vulnerable pockets in the population that stand to benefit most from better-targeted nutrition policies. Essays 1 and 2 highlight both the protective role of a mother's well-being in child nutrition and the necessary conditions that enable women to thrive. Therefore, improving the well-being of women within households is likely to yield personal benefits that may spill over to the well-being of their families and children.

Interventions such as credit and microfinance support, providing access to personal bank or mobile money accounts, and directing transfers to mothers can strengthen women's bargaining power within households. These measures can help mothers reallocate household expenditures during crises in ways that benefit children (Ajefu et al., 2024, Arif et al., 2013, DeLoach & Lamanna, 2011). In Indonesia, interventions like the Family Hope Program (Program Keluarga Harapan – PKH) incorporate a gender component, whereby the cash assistance is transferred directly to the mother's bank account (Arif et al., 2013).

On the other hand, Essay 2 also highlights the double vulnerabilities faced by women living in patriarchal cultures during times of crisis, as they are the least likely to receive nutritional support and tend to experience worse outcomes later in life (Cui et al., 2020). This further emphasizes the importance of integrating gender, age, ethnicity, and other sociodemographic information into obesity surveillance systems. Additionally, this finding demonstrates the need to involve men and community leaders in nutrition education, women's empowerment, and household decision-making, particularly in patriarchal settings (Ahmed et al., 2023, Farnworth et al., 2023, Bonis-Profumo et al., 2021).

5.3 Future research

Although Essay 1 shows the lasting impact of crises on nutritional outcomes, it remains unclear why social protection programs have failed to protect the well-being of some children in the sample. Future research needs to investigate issues related to these inefficiencies, such as whether within-household resource allocation affects equitable health outcomes. While Essay 2 answers part of the household dynamics question, understanding whether such differences originate in childhood or emerge around marriage age would clarify the timeline of when discrimination has the most lasting impact on health. Lastly, while Essay 3 focuses on the net effect of super apps on nutritional outcomes and consumption behavior, future research should examine intermediate mechanisms, such as changes in food purchasing and preparation behaviors, and the proliferation of restaurants and small-to-medium food chains. Additionally, policy research should test how modifications to the digital food environment, such as labeling, nudges, branding, and targeted incentives, affect consumer choices. Clarifying these mechanisms would enable better-targeted and scalable policy designs that improve the food environment.

5.4 Conclusion

This dissertation shows that malnutrition in LMICs is shaped by the lasting negative effects of past shocks, gender discrimination, and the rapid transformation of food environments. Across the three essays, I document the persistent scarring effect of shocks on future health (Essay 1), uneven risks of malnutrition among poorer households, poor health individuals, women, younger adults, children, and some ethnic minorities (Essay 1 and Essay 2), and food-environment changes that, without mitigating policy, raise the risk of obesity (Essay 3). These findings imply that, due to a lack of recognition and corrective policies, many countries in LMICs will face high costs of chronic-disease care, premature mortality and morbidity, and intergenerational transmission of malnutrition. The most cost-saving margin is early prevention of obesity, especially during pregnancy and in adolescence, paired with policies that incentivize innovations for a healthier food system. Progress requires not only recognition but investment in surveillance and monitoring, implementation research, and rigorous evaluation of regulatory tools. This dissertation contributes to making long-term investment in eliminating malnutrition by clarifying when and where prevention can yield the greatest health returns.

6 References

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Appendix A

Appendix A1: Laspeyres-Based Index

We construct a Laspeyres price index to calculate the real rice price in 2000 using the following approach:

1. We construct food and non-food deflators using the mean shares of the food and non-food expenditures using the IFLS 1997 survey as weights. Here we take out the rice expenditure from the calculation.
2. We also collected monthly food and non-food CPI published by Statistics Indonesia from 1997 to 2000 and matched that to the month the IFLS survey took place in each community to obtain a more accurate depiction of the national level inflation at the time of the survey. We normalize the CPI using December 2000 as the base.
3. We then calculate the household-specific deflator $P^h(t)$ using the following formula:

$$P^h(t) = W_F^{\sqrt{h}}(IFLS\ 1997)P_F(t) + \left(1 - W_F^{\sqrt{h}}(IFLS\ 1997)\right)P_{NF}(t)$$

   where t is the period between January 1997 and December 2000, when the survey took place in the IFLS communities. $W_F^{\sqrt{h}}$ is the analytical weight for each IFLS household calculated from the predictive values of the regression of household food share (excluding rice consumption) from IFLS 1997 on the log of per capita expenditure (excluding rice expenditure) and household size. $P_F(t)$ and $P_{NF}(t)$ are the price deflators for food and non-food items in period t.

Table A1. Associations between rice price changes and children's HAZ

	(1) HAZ	(2) HAZ	(3) HAZ
Explanatory variables			
Change in nominal rice price	-0.135***		
	(0.0412)		
Change in real rice price		-0.251***	
		(0.0796)	
Household experiencing income/employment loss in 1998-1999			-0.218*
			(0.130)
Children characteristics			
Female	0.118*	0.119*	0.0979
	(0.0695)	(0.0695)	(0.0672)
Age in months	0.0613***	0.0614***	0.0655***
	(0.00672)	(0.00672)	(0.00630)
Age in months (cubic term)	-1.23e-05***	-1.23e-05***	-1.33e-05***
	(1.49e-06)	(1.49e-06)	(1.41e-06)
Household characteristics			
Father's education	-0.0112	-0.0114	-0.0363
	(0.0884)	(0.0885)	(0.0841)
Mother's education	0.0171	0.0179	0.0626
	(0.0886)	(0.0887)	(0.0847)
Father smoking	0.00925	0.00900	0.0176
	(0.0725)	(0.0726)	(0.0703)
Father being Muslim	-0.573**	-0.574**	-0.596**
	(0.278)	(0.278)	(0.249)
Mother being Muslim	0.602**	0.605**	0.650***
	(0.285)	(0.285)	(0.251)
Urban	0.0243	0.0244	0.0373
	(0.109)	(0.109)	(0.103)
HH producing rice	-0.00238	-0.00500	0.0235
	(0.0852)	(0.0852)	(0.0805)
HH size	-0.0257	-0.0255	-0.0156
	(0.0177)	(0.0177)	(0.0171)
HH quantile expenditure = 1	0.256	0.254	0.218
	(0.219)	(0.219)	(0.200)
HH quantile expenditure = 2	0.296	0.295	0.274
	(0.218)	(0.218)	(0.200)
HH quantile expenditure = 3	0.332	0.331	0.357*
	(0.222)	(0.222)	(0.207)
HH quantile expenditure = 4	0.410*	0.411*	0.323
	(0.227)	(0.227)	(0.209)
HH quantile expenditure = 5, omitted	-	-	-
Community characteristics			
Available health care centers	-0.204	-0.192	-0.200
	(0.190)	(0.189)	(0.172)
Available access to clean water	-0.184*	-0.183*	-0.165*

	(0.0959)	(0.0960)	(0.0904)
Available road for motor vehicles	0.0513	0.0524	0.0169
	(0.134)	(0.134)	(0.127)
Available asphalt road	0.0114	0.0118	0.0440
	(0.102)	(0.102)	(0.0951)
Available bus stop	-0.233**	-0.231**	-0.156*
	(0.0960)	(0.0960)	(0.0938)
Experience drought or fire in 1997	0.281***	0.281***	0.258***
	(0.102)	(0.102)	(0.0969)
Available market	0.00689	0.00720	0.0953
	(0.0809)	(0.0809)	(0.0795)
Available phone office	0.0612	0.0628	0.0214
	(0.119)	(0.119)	(0.112)
Available post office	-0.0517	-0.0541	-0.0627
	(0.109)	(0.109)	(0.104)
Available bank	0.128	0.127	0.0998
	(0.0954)	(0.0955)	(0.0948)
Receive health card	0.162	0.155	0.0883
	(0.136)	(0.136)	(0.130)
Receive free rice	0.0548	0.0577	-0.000712
	(0.171)	(0.172)	(0.174)
Receive subsidized rice	-0.0265	-0.0280	-0.112
	(0.195)	(0.195)	(0.191)
Receive employment program	0.0298	0.0264	0.0669
	(0.0947)	(0.0947)	(0.0916)
Receive village grant	0.0475	0.0514	0.0805
	(0.110)	(0.110)	(0.104)
Constant	-2.465***	-2.534***	-2.500***
	(0.188)	(0.186)	(0.179)
Observations	3,338	3,338	3,596
R-squared	0.756	0.755	0.758

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. The estimation includes individual and year fixed effect. Real rice price is deflated using Laspeyres price index.

Table A2. Associations between rice price changes and children's WHZ

	(1) WHZ	(2) WHZ	(3) WHZ
Explanatory variables			
Change in nominal rice price	0.0659		
	(0.0936)		
Change in real rice price		0.143	
		(0.184)	
Household experiencing income/employment loss in 1998-1999			0.177
			(0.263)
Children characteristics			
Female	-0.189	-0.189	-0.276**
	(0.140)	(0.140)	(0.136)
Age in months	0.0369	0.0369	0.0200
	(0.0257)	(0.0257)	(0.0240)
Age in months (cubic term)	-1.22e-05	-1.23e-05	8.63e-06
	(3.27e-05)	(3.27e-05)	(3.06e-05)
Household characteristics			
Father's education	0.487***	0.486***	0.431***
	(0.167)	(0.167)	(0.158)
Mother's education	-0.121	-0.120	-0.188
	(0.170)	(0.171)	(0.162)
Father smoking	-0.245	-0.245	-0.309**
	(0.155)	(0.155)	(0.148)
Father being Muslim	0.681	0.681	0.593
	(0.436)	(0.437)	(0.412)
Mother being Muslim	-0.679	-0.676	-0.618
	(0.441)	(0.442)	(0.413)
Urban	0.294	0.292	0.262
	(0.215)	(0.215)	(0.207)
HH producing rice	0.0151	0.0157	0.0565
	(0.174)	(0.174)	(0.167)
HH size	0.00611	0.00606	0.00301
	(0.0390)	(0.0389)	(0.0375)
HH quantile expenditure = 1	0.276	0.276	0.0645
	(0.476)	(0.476)	(0.420)
HH quantile expenditure = 2	0.258	0.257	-0.0248
	(0.473)	(0.473)	(0.418)
HH quantile expenditure = 3	0.0524	0.0509	-0.182
	(0.494)	(0.493)	(0.441)
HH quantile expenditure = 4	0.308	0.306	0.116
	(0.510)	(0.510)	(0.454)
HH quantile expenditure = 5, omitted	-	-	-
Community characteristics			
Available health care centers	-0.709	-0.712	-0.735
	(0.642)	(0.642)	(0.607)
Available access to clean water	-0.0236	-0.0215	0.0320

	(0.189)	(0.190)	(0.183)
Available road for motor vehicles	0.0133	0.0159	-0.00240
	(0.309)	(0.309)	(0.296)
Available asphalt road	-0.148	-0.150	-0.0541
	(0.200)	(0.200)	(0.198)
Available bus stop	0.288	0.290	0.187
	(0.202)	(0.201)	(0.194)
Experience drought or fire in 1997	-0.348	-0.348	-0.364
	(0.248)	(0.248)	(0.225)
Available market	0.185	0.186	0.0663
	(0.166)	(0.166)	(0.163)
Available phone office	-0.158	-0.159	-0.181
	(0.236)	(0.236)	(0.226)
Available post office	-0.130	-0.132	-0.276
	(0.238)	(0.238)	(0.224)
Available bank	-0.0906	-0.0900	0.0153
	(0.207)	(0.207)	(0.200)
Receive health card	0.371	0.373	0.253
	(0.262)	(0.262)	(0.251)
Receive free rice	-0.135	-0.130	0.0500
	(0.281)	(0.282)	(0.332)
Receive subsidized rice	0.0171	0.0148	0.193
	(0.387)	(0.388)	(0.375)
Receive employment program	-0.106	-0.106	-0.137
	(0.185)	(0.185)	(0.181)
Receive village grant	-0.0848	-0.0861	-0.113
	(0.198)	(0.198)	(0.191)
Constant	-0.406	-0.376	-0.197
	(0.500)	(0.492)	(0.468)
Observations	1,268	1,268	1,376
R-squared	0.631	0.631	0.635

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. The estimation includes individual and year fixed effect. Real rice price is deflated using Laspeyres price index.

Table A3. Associations between rice price changes and children's BMIZ

	(1) BMIZ	(2) BMIZ	(3) BMIZ
Explanatory variables			
Change in nominal rice price	0.0535		
	(0.0494)		
Change in real rice price		0.112	
		(0.0973)	
Household experiencing income/employment loss in 1998-1999			0.411***
			(0.153)
Children characteristics			
Female	-0.0588	-0.0589	-0.0775
	(0.0744)	(0.0744)	(0.0720)
Age in months	-0.0139**	-0.0139**	-0.0152**
	(0.00656)	(0.00656)	(0.00621)
Age in months (cubic term)	2.37e-06	2.37e-06	2.96e-06**
	(1.51e-06)	(1.51e-06)	(1.43e-06)
Household characteristics			
Father's education	0.299***	0.298***	0.286***
	(0.0940)	(0.0941)	(0.0891)
Mother's education	-0.0569	-0.0567	-0.125
	(0.0941)	(0.0941)	(0.0902)
Father smoking	-0.1000	-0.0998	-0.123
	(0.0829)	(0.0829)	(0.0800)
Father being Muslim	0.706**	0.706**	0.442
	(0.292)	(0.292)	(0.299)
Mother being Muslim	-0.852***	-0.852***	-0.628**
	(0.295)	(0.295)	(0.296)
Urban	0.166	0.165	0.122
	(0.106)	(0.106)	(0.101)
HH producing rice	0.0197	0.0205	0.0366
	(0.0929)	(0.0928)	(0.0895)
HH size	0.0266	0.0265	0.0221
	(0.0208)	(0.0208)	(0.0201)
HH quantile expenditure = 1	-0.0884	-0.0874	-0.205
	(0.226)	(0.226)	(0.209)
HH quantile expenditure = 2	-0.121	-0.120	-0.266
	(0.226)	(0.226)	(0.209)
HH quantile expenditure = 3	-0.192	-0.191	-0.336
	(0.233)	(0.233)	(0.217)
HH quantile expenditure = 4	-0.194	-0.194	-0.298
	(0.245)	(0.245)	(0.226)
HH quantile expenditure = 5, omitted	-	-	-
Community characteristics			
Available health care centers	0.108	0.105	0.160
	(0.286)	(0.286)	(0.258)
Available access to clean water	0.0216	0.0229	0.0475

	(0.0972)	(0.0973)	(0.0917)
Available road for motor vehicles	-0.124	-0.123	-0.101
	(0.164)	(0.164)	(0.160)
Available asphalt road	0.0178	0.0170	0.0659
	(0.106)	(0.106)	(0.105)
Available bus stop	0.1000	0.101	0.0412
	(0.106)	(0.106)	(0.101)
Experience drought or fire in 1997	-0.00258	-0.00274	-0.0390
	(0.118)	(0.118)	(0.111)
Available market	0.0350	0.0359	0.00600
	(0.0888)	(0.0889)	(0.0859)
Available phone office	-0.190	-0.190	-0.205*
	(0.117)	(0.117)	(0.113)
Available post office	0.121	0.120	0.0920
	(0.120)	(0.120)	(0.111)
Available bank	-0.106	-0.106	-0.0388
	(0.110)	(0.110)	(0.105)
Receive health card	0.160	0.161	0.0789
	(0.143)	(0.143)	(0.139)
Receive free rice	-0.0343	-0.0315	0.175
	(0.182)	(0.182)	(0.199)
Receive subsidized rice	0.116	0.115	0.198
	(0.192)	(0.192)	(0.190)
Receive employment program	-0.183*	-0.183*	-0.206**
	(0.103)	(0.103)	(0.100)
Receive village grant	0.0387	0.0373	0.0363
	(0.113)	(0.113)	(0.110)
Constant	-0.278	-0.252	-0.273
	(0.234)	(0.230)	(0.219)
Observations	3,224	3,224	3,482
R-squared	0.660	0.660	0.666

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. The estimation includes individual and year fixed effect. Real rice price is deflated using Laspeyres price index.

Table A4. Interaction terms between rice price change in 1997-2000 and selected binary socioeconomic variables in HAZ, WHZ, and BMIZ models

Interaction tests (β_2)	HAZ	WHZ	BMIZ
Δ rice price × critical age	0.005		-0.032
	(0.066)		(0.079)
Δ rice price × female	0.099	-0.117	-0.095
	(0.073)	(0.170)	(0.091)
Δ rice price × high edu. mother	0.129*	-0.290*	-0.202**
	(0.075)	(0.154)	(0.084)
Δ rice price × poor	0.216	0.632	0.186
	(0.180)	(0.421)	(0.207)
Δ rice price × urban	-0.270*	0.222	0.003
	(0.153)	(0.312)	(0.163)

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from fixed effects panel data regression models, as explained in equation 2.2, with robust standard errors in parentheses. WHZ can only be estimated among children aged 0-31 months old in 1997.

Figure A1. Heterogenous effects of nominal rice price changes in 1997-2000 on child nutrition status

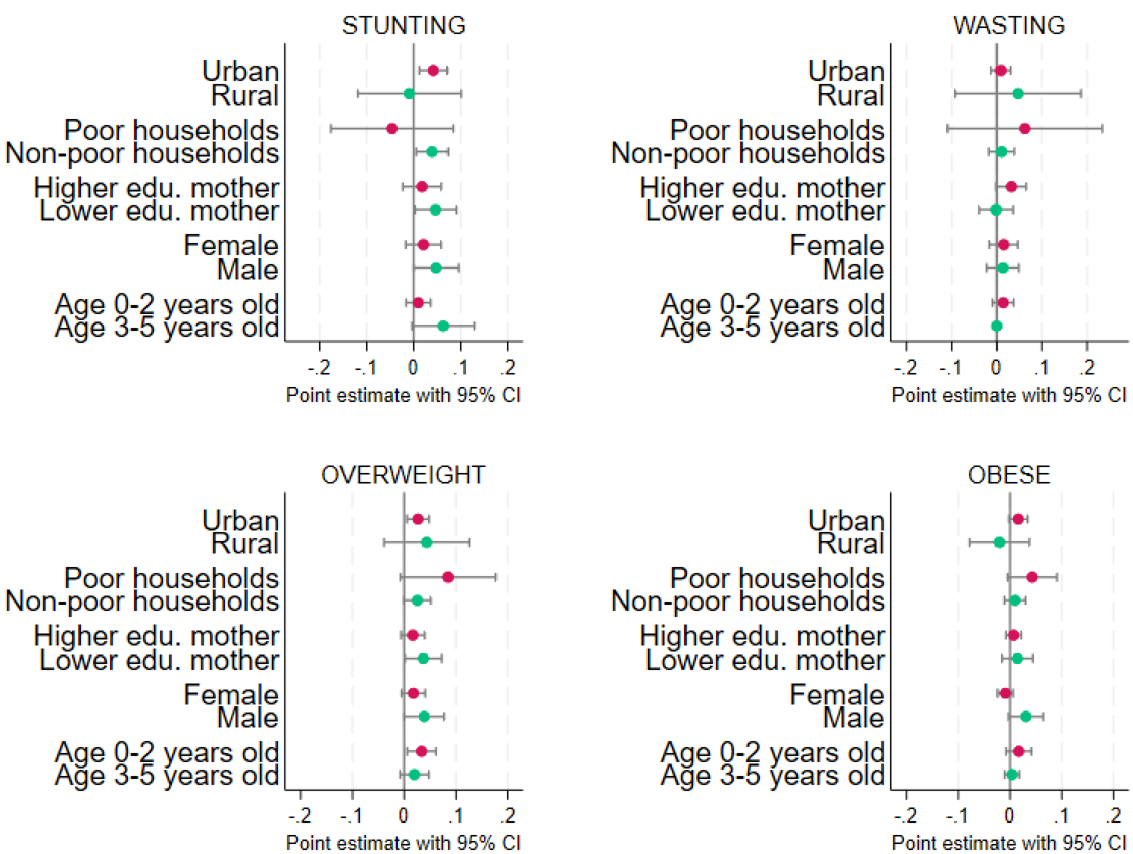


Table A5. Interaction terms between rice price change in 1997-2000 and selected binary socioeconomic variables in nutritional status models

Nominal	Stunting	Wasting	Overweight	Obese
Δ rice price × critical age	-0.053		0.014	0.013
	(0.036)		(0.020)	(0.015)
Δ rice price × female	-0.026	0.002	-0.021	-0.040**
	(0.032)	(0.024)	(0.022)	(0.019)
Δ rice price × high edu. mother	-0.028	0.033	-0.020	-0.007
	(0.032)	(0.026)	(0.022)	(0.017)
Δ rice price × poor	-0.085	0.051	0.059	0.033
	(0.079)	(0.105)	(0.057)	(0.031)
Δ rice price × urban	0.051	-0.037	-0.017	0.036
	(0.058)	(0.073)	(0.043)	(0.031)

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from fixed effects panel data regression models, as explained in equation 2.2, with robust standard errors in parentheses. Wasting can only be estimated among children aged 0-31 months old in 1997.

Table A6. Associations between rice price changes during the crisis and adult anthropometric outcomes in 2014

	(1) Height	(2) BMI	(3) Overweight	(4) Obese	(5) Height	(6) BMI	(7) Overweight	(8) Obese
Explanatory variables								
Change in nominal rice	-0.645***	0.196	0.0123	0.0121				
price	(0.232)	(0.167)	(0.0134)	(0.0132)				
					-1.200***	0.432	0.0286	0.0270
Change in real rice price					(0.450)	(0.328)	(0.0265)	(0.0259)
Children characteristics								
Age	-3.176***	0.0196	0.000340	0.000476	-3.183***	0.0208	0.000392	0.000545
	(0.354)	(0.186)	(0.0186)	(0.0121)	(0.354)	(0.186)	(0.0186)	(0.0121)
Female	-7.706***	0.442***	0.0554***	0.0219**	-7.706***	0.442***	0.0554***	0.0219**
	(0.267)	(0.140)	(0.0137)	(0.00925)	(0.268)	(0.140)	(0.0137)	(0.00925)
Age in months at baseline	0.525***	0.00812	0.00255	0.00110	0.525***	0.00798	0.00255	0.00109
	(0.0349)	(0.0170)	(0.00161)	(0.00107)	(0.0349)	(0.0170)	(0.00161)	(0.00106)
HAZ score at baseline [a]	1.609***	-0.0384	0.00800*	0.00656**	1.608***	-0.0389	0.00796*	0.00653**
	(0.101)	(0.0485)	(0.00447)	(0.00320)	(0.101)	(0.0485)	(0.00447)	(0.00320)
In-utero/just born cohort, omitted	-	-	-	-	-	-	-	-
Cohort 0-2 years old	94.83***	4.576***	0.171***	0.0699*	94.85***	4.571***	0.171***	0.0697*
	(1.113)	(0.591)	(0.0587)	(0.0379)	(1.113)	(0.591)	(0.0587)	(0.0379)
Cohort 3-5 years old	88.15***	5.077***	0.195***	0.0638	88.17***	5.073***	0.195***	0.0636
	(1.248)	(0.686)	(0.0735)	(0.0472)	(1.248)	(0.686)	(0.0735)	(0.0472)
Household characteristics								
Father's education	0.285	-0.0250	-0.0157	-0.00990	0.283	-0.0277	-0.0160	-0.0101
	(0.339)	(0.189)	(0.0171)	(0.0121)	(0.339)	(0.189)	(0.0171)	(0.0121)
Mother's education	0.452	0.129	0.0244	-0.0115	0.452	0.131	0.0246	-0.0113
	(0.365)	(0.194)	(0.0191)	(0.0130)	(0.365)	(0.194)	(0.0191)	(0.0130)
Father smoking	0.228	-0.289*	-0.0114	-0.0136	0.228	-0.288*	-0.0114	-0.0136

	(0.279)	(0.151)	(0.0146)	(0.00995)	(0.279)	(0.151)	(0.0146)	(0.00995)
Father being Muslim	1.244	-0.189	-0.0541	-0.0176	1.245	-0.184	-0.0537	-0.0172
	(2.131)	(1.126)	(0.0582)	(0.0246)	(2.134)	(1.124)	(0.0580)	(0.0245)
Mother being Muslim	-2.067	-0.214	0.0314	-0.000873	-2.057	-0.213	0.0315	-0.000809
	(2.135)	(1.117)	(0.0576)	(0.0237)	(2.138)	(1.115)	(0.0575)	(0.0236)
Urban	0.436	0.517**	0.0227	0.0488***	0.429	0.514**	0.0225	0.0486***
	(0.392)	(0.229)	(0.0208)	(0.0150)	(0.392)	(0.228)	(0.0208)	(0.0150)
HH producing rice	0.315	0.0768	0.0136	0.00120	0.306	0.0789	0.0137	0.00133
	(0.346)	(0.178)	(0.0178)	(0.0112)	(0.346)	(0.178)	(0.0177)	(0.0112)
HH size	0.0547	0.000506	0.00269	-0.00270	0.0556	0.000513	0.00269	-0.00270
	(0.0652)	(0.0349)	(0.00345)	(0.00237)	(0.0652)	(0.0349)	(0.00345)	(0.00237)
HH quantile expenditure =	0.483	-0.594**	-0.0497*	-0.00447	0.466	-0.592**	-0.0496*	-0.00436
1	(0.563)	(0.272)	(0.0267)	(0.0175)	(0.563)	(0.271)	(0.0267)	(0.0175)
HH quantile expenditure =	0.553	-0.193	-0.0134	0.0254	0.542	-0.191	-0.0134	0.0255
2	(0.547)	(0.266)	(0.0258)	(0.0174)	(0.548)	(0.266)	(0.0258)	(0.0174)
HH quantile expenditure =	0.910	-0.488*	-0.0395	-0.00670	0.902	-0.487*	-0.0395	-0.00660
3	(0.556)	(0.255)	(0.0249)	(0.0165)	(0.557)	(0.255)	(0.0249)	(0.0165)
HH quantile expenditure =	0.870	-0.205	0.00517	0.00223	0.865	-0.205	0.00515	0.00223
4	(0.572)	(0.258)	(0.0250)	(0.0159)	(0.572)	(0.258)	(0.0250)	(0.0159)
HH quantile expenditure = 5	-	-	-	-	-	-	-	-
Community characteristics								
Available health care	3.518**	-1.375**	-0.0302	-0.0736	3.580**	-1.376**	-0.0299	-0.0735
centers	(1.752)	(0.664)	(0.0701)	(0.0602)	(1.752)	(0.663)	(0.0701)	(0.0601)
Available access to clean	-0.753**	0.158	0.0173	-0.00859	-0.752**	0.166	0.0179	-0.00810
water	(0.329)	(0.180)	(0.0180)	(0.0121)	(0.329)	(0.180)	(0.0180)	(0.0121)
Available road for motor	-0.255	0.103	0.00440	0.0120	-0.252	0.105	0.00452	0.0120
vehicles	(0.616)	(0.296)	(0.0316)	(0.0180)	(0.616)	(0.296)	(0.0316)	(0.0180)
Available asphalt road	0.529	-0.223	-0.0120	-0.00613	0.529	-0.227	-0.0123	-0.00640
	(0.408)	(0.208)	(0.0212)	(0.0134)	(0.408)	(0.208)	(0.0212)	(0.0134)

Available bus stop	0.0917	0.212	0.0193	0.0168	0.0981	0.217	0.0197	0.0171
	(0.370)	(0.192)	(0.0188)	(0.0131)	(0.370)	(0.192)	(0.0188)	(0.0131)
Experience drought or fire	-0.170	-0.149	0.00341	0.0119	-0.176	-0.152	0.00311	0.0116
in 1997	(0.455)	(0.235)	(0.0227)	(0.0167)	(0.455)	(0.235)	(0.0227)	(0.0167)
Available market	-0.0601	0.0446	0.0288*	0.0118	-0.0594	0.0482	0.0291*	0.0121
	(0.309)	(0.164)	(0.0162)	(0.0106)	(0.309)	(0.164)	(0.0162)	(0.0107)
Available phone office	-0.270	-0.116	-0.000162	0.000991	-0.263	-0.117	-0.000201	0.000933
	(0.389)	(0.222)	(0.0208)	(0.0153)	(0.389)	(0.222)	(0.0208)	(0.0153)
Available post office	-0.664	0.249	0.00977	0.0119	-0.679	0.247	0.00951	0.0117
	(0.453)	(0.262)	(0.0237)	(0.0172)	(0.453)	(0.262)	(0.0237)	(0.0172)
Available bank	0.710*	-0.443**	-0.0285	-0.0410***	0.708*	-0.444**	-0.0286	-0.0411***
	(0.394)	(0.210)	(0.0206)	(0.0149)	(0.394)	(0.210)	(0.0206)	(0.0149)
Receive health card	-0.152	0.405	-0.0376	0.0159	-0.177	0.404	-0.0378	0.0158
	(0.565)	(0.275)	(0.0309)	(0.0187)	(0.564)	(0.275)	(0.0309)	(0.0187)
Receive free rice	-0.0684	0.339	0.0869**	0.0332**	-0.0485	0.356	0.0885**	0.0344**
	(0.854)	(0.357)	(0.0372)	(0.0156)	(0.855)	(0.357)	(0.0372)	(0.0157)
Receive subsidized rice	2.233***	0.0765	0.00244	0.0244	2.232***	0.0657	0.00151	0.0236
	(0.766)	(0.308)	(0.0337)	(0.0163)	(0.767)	(0.308)	(0.0338)	(0.0164)
Receive employment	-0.463	0.122	0.0142	0.00702	-0.480	0.123	0.0141	0.00703
program	(0.363)	(0.211)	(0.0196)	(0.0138)	(0.363)	(0.210)	(0.0196)	(0.0137)
Receive village grant	0.250	0.191	0.00318	0.00286	0.263	0.188	0.00305	0.00271
	(0.424)	(0.239)	(0.0223)	(0.0156)	(0.424)	(0.239)	(0.0223)	(0.0156)
Constant	114.3***	15.93***	-0.121	-0.0220	113.7***	16.10***	-0.111	-0.0119
	(5.307)	(2.750)	(0.273)	(0.181)	(5.286)	(2.742)	(0.272)	(0.181)
Observations	2,349	2,313	2,313	2,313	2,349	2,313	2,313	2,313
R-squared	0.979	0.349	0.126	0.063	0.979	0.349	0.126	0.064

Notes: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from OLS models with 2014 anthropometric outcomes as dependent variables. Robust standard errors shown in parentheses. All models estimated with baseline (1997) control variables and regional fixed effects included. [a] For the in-utero and just born cohort, we use IFLS 2000 data to calculate baseline HAZ.

Table A7. Interaction terms between rice price change in 1997-2000 and adult anthropometric outcomes in 2014

Interaction tests (β_2)	Height	BMI	Overweight	Obese
Δ rice price × 0-2 years old	0.841*	0.048	-0.009	-0.007
	(0.485)	(0.272)	(0.019)	(0.018)
Δ rice price × 3-5 years old	-0.133	0.597	0.050	0.091***
	(0.506)	(0.370)	(0.037)	(0.031)
Δ rice price × female	-0.305	0.435	0.024	0.029
	(0.429)	(0.310)	(0.026)	(0.025)
Δ rice price × high edu. mother	0.214	-0.001	0.016	0.013
	(0.447)	(0.340)	(0.026)	(0.026)
Δ rice price × poor	-0.101	0.261	-0.006	0.003
	(0.870)	(0.455)	(0.042)	(0.029)
Δ rice price × urban	1.015	-0.180	-0.028	-0.001
	(0.638)	(0.331)	(0.032)	(0.023)

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from fixed effects panel data regression models, as explained in equation 2.2, with robust standard errors in parentheses.

Appendix B

Marriage customs and nutritional status of men and women

Table B1: Associations between ethnicity-based marriage customs and actual marriage practices

	Actual Matrilocality		Actual Patrilocality		Actual Bridewealth	
	(1)	(2)	(3)	(4)	(5)	(6)
Ethnic matrilocal	0.128***	0.099***	-0.078***	-0.054***		
	(0.015)	(0.017)	(0.013)	(0.015)		
Ethnic patrilocal	-0.117***	-0.088***	0.076***	0.049***		
	(0.012)	(0.014)	(0.011)	(0.012)		
Community matrilocal		0.053***		-0.051***		
		(0.011)		(0.010)		
Community patrilocal		-0.123***		0.071***		
		(0.015)		(0.013)		
Ethnic bridewealth					0.012**	0.016***
					(0.006)	(0.006)
Community bridewealth						0.008*
						(0.004)
Observations	9421	7802	8945	7431	26626	23408
$R2$	0.037	0.061	0.020	0.034	0.536	0.571
Mean outcome	.279	.275	.299	.294	.302	.315

Note: *** p<0.01, ** p<0.05, * p<0.10. Regression models 1-4 were completed for a subset of married women above 50 years of age. Regression models 5-6 were completed for a subset of ever-married women and men above 50 years of age because the survey question was focused on the bridewealth payment history of couples. Bridewealth payment includes house, money, jewelry, and cattle. Analysis was also done on the married adult population at the age of 25-49 and the results remain unchanged.

Table B2: Development of adult nutritional status in Indonesia (1993-2014)

	IFLS 1993	IFLS 1997	IFLS 2000	IFLS 2007	IFLS 2014
Male					
Body mass index(BMI)	21.14	21.19	21.31	22.00	22.63
	(2.99)	(3.01)	(3.20)	(3.64)	(3.91)
Underweight (BMI<18)	0.11	0.11	0.11	0.09	0.08
	(0.32)	(0.31)	(0.32)	(0.29)	(0.28)
Overweight (BMI≥23)	0.22	0.22	0.24	0.32	0.41
	(0.41)	(0.42)	(0.43)	(0.47)	(0.49)
Obesity (BMI>27)	0.04	0.05	0.06	0.10	0.14
	(0.21)	(0.21)	(0.24)	(0.29)	(0.34)
Female					
Body mass index (BMI)	21.86	22.20	22.40	23.39	24.60
	(3.67)	(3.87)	(3.98)	(4.42)	(4.73)
Underweight (BMI<18)	0.12	0.11	0.10	0.08	0.06
	(0.33)	(0.31)	(0.30)	(0.27)	(0.23)
Overweight (BMI≥23)	0.33	0.35	0.38	0.48	0.60
	(0.47)	(0.48)	(0.49)	(0.50)	(0.49)
Obesity (BMI>27)	0.10	0.12	0.12	0.19	0.28
	(0.30)	(0.32)	(0.33)	(0.39)	(0.45)
Observations	11841	15337	20285	24268	27464

Table B3: Nutritional status of male and female adults based on marriage customs (data pooled across survey waves)

	Neolocal	Matrilocal	Patrilocal	No bridewealth	Bridewealth	Neolocal-bridewealth	Matrilocal-bridewealth	Patrilocal-bridewealth
Male								
Body mass index	21.77	21.82	22.19	21.76	22.08	21.74	21.83	22.19
	(3.45)	(3.56)	(3.71)	(3.49)	(3.71)	(3.50)	(3.37)	(3.82)
Underweight (BMI<18)	0.10	0.10	0.09	0.10	0.10	0.12	0.08	0.10
	(0.29)	(0.30)	(0.29)	(0.30)	(0.30)	(0.33)	(0.27)	(0.30)
Overweight (BMI≥23)	0.29	0.31	0.35	0.30	0.34	0.29	0.29	0.36
	(0.46)	(0.46)	(0.48)	(0.46)	(0.47)	(0.46)	(0.46)	(0.48)
Obesity (BMI>27)	0.08	0.08	0.11	0.08	0.11	0.09	0.07	0.12
	(0.28)	(0.27)	(0.31)	(0.28)	(0.31)	(0.28)	(0.26)	(0.32)
Number of samples	28084	3791	8257	32438	7694	563	1706	5425
Female								
Body mass index	23.16	23.36	23.34	23.09	23.40	22.26	22.89	23.70
	(4.36)	(4.38)	(4.40)	(4.35)	(4.48)	(4.14)	(4.31)	(4.53)
Underweight (BMI<18)	0.08	0.07	0.08	0.09	0.08	0.14	0.10	0.07
	(0.28)	(0.26)	(0.27)	(0.28)	(0.28)	(0.35)	(0.29)	(0.26)
Overweight (BMI≥23)	0.45	0.48	0.47	0.45	0.48	0.39	0.43	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Obesity (BMI>27)	0.18	0.18	0.19	0.17	0.19	0.14	0.16	0.21
	(0.38)	(0.39)	(0.39)	(0.38)	(0.40)	(0.34)	(0.37)	(0.41)
Number of samples	33207	4964	9516	38470	9217	649	2248	6320
Observations	61291	8755	17773	70908	16911	1212	3954	11745

Table B4: Descriptive statistics of covariates by ethnicity-based marriage customs

	Locality Cultures						Bridewealth (BP)		
	A. Neolocal	B. Matrilocal	C. Patrilocal	A-B	A-C	B-C	D. No BP	E. BP	D-E
Demography									
Female	0.53	0.54	0.52	-0.0144**	0.00796	0.0223***	0.52	0.53	-0.00591
	(0.50)	(0.50)	(0.50)	(-2.62)	(1.92)	(3.56)	(0.50)	(0.50)	(-1.45)
Age in year	37.63	37.88	36.75	-0.250	0.877***	1.127***	37.82	36.75	1.068***
	(12.18)	(12.26)	(11.96)	(-1.87)	(8.73)	(7.42)	(12.46)	(11.95)	(10.59)
Age in year squared	1564.45	1585.20	1493.95	-20.75	70.50***	91.25***	1585.68	1493.48	92.21***
	(991.97)	(998.01)	(961.61)	(-1.90)	(8.64)	(7.45)	(1018.84)	(958.40)	(11.22)
Years of schooling	5.50	5.69	5.94	-0.195***	-0.437***	-0.242***	5.56	5.87	-0.316***
	(4.47)	(4.62)	(4.70)	(-3.95)	(-11.67)	(-4.12)	(4.53)	(4.60)	(-8.53)
Being married	0.80	0.75	0.78	0.0541***	0.0211***	-0.0330***	0.78	0.76	0.0270***
	(0.40)	(0.43)	(0.41)	(12.19)	(6.33)	(-6.22)	(0.41)	(0.43)	(8.01)
Have work in the past week	0.73	0.68	0.73	0.0541***	-0.00503	-0.0591***	0.72	0.69	0.0278***
	(0.44)	(0.47)	(0.44)	(11.00)	(-1.37)	(-10.42)	(0.45)	(0.46)	(7.51)
Live in urban areas	0.53	0.51	0.51	0.0242***	0.0207***	-0.00350	0.53	0.55	-0.0246***
	(0.50)	(0.50)	(0.50)	(4.41)	(5.01)	(-0.56)	(0.50)	(0.50)	(-6.05)
Religion: Islam	0.97	0.90	0.64	0.0767***	0.334***	0.257***	0.90	0.81	0.0900***
	(0.16)	(0.31)	(0.48)	(37.02)	(149.10)	(47.50)	(0.30)	(0.39)	(35.17)
History of smoking	0.33	0.31	0.33	0.0222***	0.00778*	-0.0144*	0.33	0.33	0.00524
	(0.47)	(0.46)	(0.47)	(4.30)	(1.99)	(-2.46)	(0.47)	(0.47)	(1.37)
Households variables									
Household size	4.45	5.06	4.72	-0.606***	-0.269***	0.337***	4.58	4.90	-0.313***
	(1.95)	(2.24)	(2.10)	(-27.73)	(-16.36)	(12.45)	(2.04)	(2.22)	(-18.53)
Real expenditure/capita	13.29	13.35	13.42	-0.0639***	-0.137***	-0.0732***	13.30	13.38	-0.0787***
	(0.78)	(0.79)	(0.76)	(-7.29)	(-20.96)	(-7.38)	(0.80)	(0.78)	(-11.94)
Female household head	0.16	0.18	0.13	-0.0122	0.0382***	0.0504***	0.16	0.15	0.00955*
	(0.37)	(0.38)	(0.33)	(-1.87)	(8.16)	(7.22)	(0.36)	(0.35)	(2.05)
Working female	0.31	0.30	0.32	0.0174***	-0.00569	-0.0231***	0.31	0.28	0.0213***
	(0.46)	(0.46)	(0.47)	(3.43)	(-1.48)	(-3.97)	(0.46)	(0.45)	(5.69)
Share of staple food expenditure	0.14	0.15	0.14	-0.0134***	-0.00440***	0.00900***	0.14	0.14	0.00376***
	(0.12)	(0.13)	(0.13)	(-10.00)	(-4.38)	(5.49)	(0.12)	(0.12)	(3.65)
Share of cooking oil expenditure	0.02	0.03	0.02	-0.00108***	0.00226***	0.00335***	0.02	0.02	0.00152***
	(0.03)	(0.03)	(0.02)	(-3.80)	(11.12)	(11.86)	(0.02)	(0.02)	(7.48)
Share of meat/fish expenditure	0.10	0.12	0.11	-0.0211***	-0.0113***	0.00981***	0.10	0.12	-0.0164***
	(0.08)	(0.09)	(0.08)	(-23.76)	(-17.00)	(9.12)	(0.08)	(0.09)	(-24.13)
Own TV/HH appliances	0.88	0.89	0.88	-0.00565	0.00215	0.00780	0.87	0.89	-0.0161***
	(0.32)	(0.32)	(0.33)	(-1.59)	(0.80)	(1.91)	(0.33)	(0.31)	(-6.00)
Share of food expenditure	0.55	0.57	0.56	-0.0137***	-0.00723***	0.00644**	0.55	0.57	-0.0162***
	(0.17)	(0.17)	(0.17)	(-7.37)	(-5.17)	(2.96)	(0.17)	(0.17)	(-11.51)
Community variables									
Garbage/manure exposure	0.26	0.34	0.33	-0.0825***	-0.0658***	0.0167*	0.27	0.36	-0.0905***
	(0.44)	(0.47)	(0.47)	(-14.85)	(-15.60)	(2.47)	(0.44)	(0.48)	(-21.53)
Pop. density (population/size of district)	2.47	1.92	2.25	0.556***	0.220***	-0.336***	2.39	2.10	0.283***
	(2.29)	(2.72)	(2.55)	(20.81)	(10.94)	(-9.88)	(2.37)	(2.74)	(13.69)
Farmland share	0.27	0.25	0.52	0.0206***	-0.248***	-0.269***	0.33	0.18	0.151***
	(0.34)	(0.33)	(5.00)	(5.48)	(-12.40)	(-5.17)	(2.38)	(0.30)	(8.46)
Clean water access	0.27	0.39	0.29	-0.127***	-0.0207***	0.106***	0.29	0.22	0.0776***
	(0.44)	(0.49)	(0.45)	(-25.16)	(-5.52)	(17.72)	(0.46)	(0.41)	(20.77)
Clean toilet access	0.72	0.65	0.73	0.0696***	-0.0107*	-0.0803***	0.70	0.72	-0.0246***
	(0.45)	(0.48)	(0.45)	(12.21)	(-2.52)	(-12.21)	(0.46)	(0.45)	(-5.73)
Electricity access	0.98	0.99	0.99	-0.0152***	-0.0124***	0.00286*	0.98	0.99	-0.0169***
	(0.14)	(0.08)	(0.09)	(-9.96)	(-11.00)	(2.54)	(0.15)	(0.08)	(-14.65)
Car road available	0.94	0.96	0.97	-0.0144***	-0.0214***	-0.00699**	0.94	0.96	-0.0150***

	(0.23)	(0.20)	(0.18)	(-5.69)	(-11.55)	(-2.89)	(0.23)	(0.20)	(-8.13)
Health facility available	0.91	0.90	0.88	0.00675*	0.0288***	0.0221***	0.92	0.87	0.0532***
	(0.28)	(0.29)	(0.32)	(2.12)	(11.67)	(5.51)	(0.27)	(0.34)	(22.35)
Nutritional status									
Body Mass Index	22.52	22.69	22.81	-0.172***	-0.285***	-0.113*	22.47	22.80	-0.323***
	(4.03)	(4.12)	(4.13)	(-3.73)	(-8.24)	(-2.09)	(4.03)	(4.20)	(-9.42)
Underweight (BMI<18)	0.09	0.08	0.09	0.00539	0.00394	-0.00145	0.09	0.09	0.00325
	(0.29)	(0.28)	(0.28)	(1.66)	(1.62)	(-0.40)	(0.29)	(0.29)	(1.33)
Overweight (BMI≥23)	0.38	0.40	0.42	-0.0227***	-0.0356***	-0.0129*	0.38	0.41	-0.0352***
	(0.49)	(0.49)	(0.49)	(-4.09)	(-8.57)	(-2.00)	(0.48)	(0.49)	(-8.57)
Obesity (BMI>27)	0.13	0.14	0.15	-0.00508	-0.0168***	-0.0117*	0.13	0.15	-0.0224***
	(0.34)	(0.35)	(0.36)	(-1.30)	(-5.71)	(-2.53)	(0.34)	(0.36)	(-7.76)
Observations		92929		74101	83427	28330	105839		105839

Note: *** p<0.01, ** p<0.05, * p<0.10. The differences in covariates between locality and bridewealth customs are tested using a t-test.

Table B5: Associations between ethnicity-based marriage customs and adult BMI (full model results for models without female interaction terms, panel D of Table 3.1)

	Random Effect		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Marriage customs						
Patrilocality	0.140**		0.132**		-0.018	-0.079
	(0.061)		(0.063)		(0.077)	(0.079)
Matrilocality	0.146**		0.186**		0.045	0.051
	(0.073)		(0.076)		(0.081)	(0.083)
Bridewealth		0.180***		0.213***	0.227***	0.304***
		(0.055)		(0.057)	(0.074)	(0.076)
Individual characteristics						
Female	1.084***	1.013***	0.678***	0.670***	1.084***	0.679***
	(0.051)	(0.047)	(0.063)	(0.057)	(0.051)	(0.063)
Age in year	0.347***	0.342***	0.355***	0.347***	0.347***	0.355***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age in year squared	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling	0.016***	0.018***	-0.004	-0.004	0.016***	-0.004
	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Being married	0.399***	0.400***	0.134***	0.140***	0.401***	0.135***
	(0.038)	(0.035)	(0.046)	(0.044)	(0.038)	(0.046)
Have work in the past week	0.031	0.041	0.072**	0.076***	0.032	0.072**
	(0.029)	(0.027)	(0.031)	(0.029)	(0.029)	(0.031)
Live in urban areas	0.410***	0.466***	0.024	0.038	0.404***	0.022
	(0.038)	(0.036)	(0.055)	(0.055)	(0.038)	(0.055)
Religion: Islam	-0.239***	-0.364***	0.060	0.067	-0.281***	0.061
	(0.071)	(0.057)	(0.148)	(0.141)	(0.071)	(0.148)
History of smoking	-0.531***	-0.553***	-0.209***	-0.220***	-0.532***	-0.209***
	(0.039)	(0.036)	(0.047)	(0.044)	(0.039)	(0.047)
Household characteristics						
Household size	0.028***	0.027***	0.009	0.009	0.027***	0.009
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)
Real expenditure/capita	0.334***	0.352***	0.176***	0.183***	0.334***	0.176***
	(0.019)	(0.018)	(0.021)	(0.020)	(0.019)	(0.021)
Share of staple food expenditure	-0.115	-0.160*	0.211**	0.157	-0.110	0.211**
	(0.097)	(0.090)	(0.103)	(0.097)	(0.097)	(0.103)
Share of cooking oil expenditure	0.675*	0.630*	0.418	0.323	0.683*	0.418
	(0.385)	(0.367)	(0.411)	(0.397)	(0.385)	(0.411)
Share of meat/fish expenditure	-0.053	0.093	-0.149	-0.114	-0.059	-0.147
	(0.139)	(0.130)	(0.148)	(0.140)	(0.139)	(0.148)
Own TV/HH appliances	0.051*	0.068**	-0.074**	-0.060**	0.050*	-0.074**
	(0.029)	(0.027)	(0.031)	(0.029)	(0.029)	(0.031)

Share of food expenditure	-0.296***	-0.326***	-0.130*	-0.124*	-0.298***	-0.130*
	(0.074)	(0.070)	(0.077)	(0.074)	(0.074)	(0.077)
Community characteristics						
Garbage/manure exposure	0.032	0.003	0.072***	0.051**	0.031	0.072***
	(0.022)	(0.021)	(0.023)	(0.022)	(0.022)	(0.023)
Pop. density (pop/hasq)	0.031***	0.032***	0.008*	0.007	0.032***	0.008*
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Farmland share	0.002	0.002	0.004	0.004	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Clean water access	0.019	0.019	0.002	-0.010	0.025	0.003
	(0.025)	(0.024)	(0.027)	(0.026)	(0.025)	(0.027)
Clean toilet access	0.049**	0.060***	0.010	0.016	0.048**	0.010
	(0.023)	(0.022)	(0.024)	(0.023)	(0.023)	(0.024)
Electricity access	-0.123*	-0.103*	-0.237***	-0.221***	-0.125*	-0.237***
	(0.064)	(0.060)	(0.070)	(0.067)	(0.064)	(0.070)
Car road available	0.020	0.015	0.019	0.016	0.020	0.019
	(0.039)	(0.037)	(0.043)	(0.041)	(0.039)	(0.043)
Health facility available	-0.235***	-0.201***	-0.254***	-0.246***	-0.233***	-0.254***
	(0.042)	(0.040)	(0.044)	(0.042)	(0.042)	(0.044)
Time averages						
Mean years of schooling			0.024***	0.028***		0.025***
			(0.007)	(0.007)		(0.007)
Mean being married			0.907***	0.797***		0.914***
			(0.076)	(0.068)		(0.076)
Mean have worked in the past week			-0.204***	-0.150**		-0.193**
			(0.079)	(0.069)		(0.079)
Mean live in urban areas			0.311***	0.366***		0.290***
			(0.084)	(0.080)		(0.084)
Mean household size			0.041**	0.035**		0.040**
			(0.016)	(0.014)		(0.016)
Mean real expenditure/capita			0.516***	0.494***		0.524***
			(0.054)	(0.047)		(0.054)
Mean religion: Islam			-0.346**	-0.441***		-0.403**
			(0.170)	(0.155)		(0.170)
Mean history of smoking			-0.914***	-0.854***		-0.918***
			(0.081)	(0.074)		(0.081)
Mean share of staple food expenditure			-1.534***	-1.273***		-1.482***
			(0.340)	(0.284)		(0.340)
Mean share of cooking oil expenditure			4.604***	3.801***		4.656***
			(1.452)	(1.196)		(1.454)
Mean share of meat/fish expenditure			1.401***	1.875***		1.296***
			(0.487)	(0.400)		(0.486)

Mean own TV/hh appliances			0.738***	0.572***		0.727***
			(0.102)	(0.088)		(0.102)
Mean share of food expenditure			-0.796***	-0.857***		-0.825***
			(0.244)	(0.209)		(0.244)
Mean garbage/manure exposure			-0.287***	-0.339***		-0.293***
			(0.068)	(0.061)		(0.068)
Mean pop. density (pop/hasq)			0.093***	0.081***		0.097***
			(0.015)	(0.013)		(0.015)
Mean farmland share			-0.013	-0.012		-0.005
			(0.015)	(0.014)		(0.015)
Mean clean water access			-0.013	0.065		0.032
			(0.069)	(0.063)		(0.070)
Mean clean toilet access			0.037	0.013		0.034
			(0.076)	(0.067)		(0.076)
Mean electricity access			0.851***	0.485**		0.809***
			(0.246)	(0.190)		(0.245)
Mean car road available			-0.184	-0.220*		-0.185
			(0.149)	(0.126)		(0.149)
Mean health facility available			0.544***	0.638***		0.566***
			(0.112)	(0.104)		(0.112)
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	22.412	22.35	22.412	22.35	22.412	22.412

Note: *** p<0.01, ** p<0.05, * p<0.10.

Table B6: Associations between ethnicity-based marriage customs and adult BMI (without consumption controls)

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Patrilocality	0.258***		0.202***		0.165*	0.028
	(0.076)		(0.077)		(0.096)	(0.096)
Matrilocality	0.053		0.059		-0.002	-0.047
	(0.095)		(0.097)		(0.105)	(0.106)
Bridewealth		0.146**		0.179**	0.125	0.241**
		(0.072)		(0.073)	(0.096)	(0.096)
Panel B. Women						
Patrilocality	0.013		-0.008		-0.199*	-0.293***
	(0.087)		(0.087)		(0.108)	(0.109)
Matrilocality	0.207*		0.275**		0.065	0.084
	(0.107)		(0.109)		(0.119)	(0.12)
Bridewealth		0.201**		0.248***	0.313***	0.418***
		(0.082)		(0.082)	(0.109)	(0.11)
Panel C: Difference between women and men (female interaction term)						
Patrilocality	-0.245**		-0.210**		-0.364***	-0.321**
	(0.108)		(0.106)		(0.136)	(0.134)
Matrilocality	0.154		0.216		0.067	0.132
	(0.143)		(0.141)		(0.157)	(0.155)
Bridewealth		0.054		0.069	0.188	0.177
		(0.108)		(0.107)	(0.144)	(0.142)
Panel D: Overall associations among adults (without including female interaction term)						
Patrilocality	0.130**		0.092		-0.029	-0.143*
	(0.061)		(0.063)		(0.077)	(0.079)
Matrilocality	0.137*		0.177**		0.036	0.025
	(0.073)		(0.076)		(0.081)	(0.083)
Bridewealth		0.175***		0.216***	0.227***	0.338***
		(0.055)		(0.057)	(0.074)	(0.076)
Observations	65560	74329	65560	74329	65560	65560
Mean outcome	22.412	22.35	22.412	22.35	22.412	22.412

Note: *** p<0.01, ** p<0.05, * p<0.10.

Table B7: Associations between ethnicity-based marriage customs and adult height

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Associations among men						
Patrilocality	-0.012		-0.295**		0.073	-0.184
	(0.136)		(0.137)		(0.188)	(0.189)
Matrilocality	-0.228		-0.217		-0.183	-0.157
	(0.209)		(0.209)		(0.215)	(0.214)
Bridewealth		-0.119		-0.285**	-0.100	-0.133
		(0.139)		(0.139)	(0.195)	(0.195)
Panel B. Associations among women						
Patrilocality	-0.055		-0.315**		0.419**	0.197
	(0.122)		(0.125)		(0.163)	(0.166)
Matrilocality	-0.135		-0.109		0.186	0.236
	(0.155)		(0.158)		(0.176)	(0.179)
Bridewealth		-0.448***		-0.593***	-0.712***	-0.767***
		(0.113)		(0.115)	(0.16)	(0.163)
Panel C. Difference between women and men (female interaction term)						
Patrilocality	-0.042		-0.020		0.346	0.381
	(0.177)		(0.176)		(0.244)	(0.242)
Matrilocality	0.093		0.108		0.369	0.393
	(0.264)		(0.261)		(0.283)	(0.280)
Bridewealth		-0.329*		-0.308*	-0.612**	-0.634**
		(0.178)		(0.177)	(0.254)	(0.252)
Panel D: Overall associations among adults without female interaction term						
Patrilocality	-0.034		-0.305***		0.257**	0.020
	(0.094)		(0.097)		(0.126)	(0.129)
Matrilocality	-0.178		-0.158		0.009	0.049
	(0.126)		(0.129)		(0.134)	(0.137)
Bridewealth		-0.293***		-0.447***	-0.423***	-0.468***
		(0.089)		(0.091)	(0.124)	(0.127)
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	155.313	155.348	155.313	155.348	155.313	155.313

Note: *** p<0.01, ** p<0.05, * p<0.10. Coefficients from panel data regression models with robust standard errors in parentheses. Height is measured in cm. Individual, household, and community control variables were included in estimation. RE, random effects estimator. CRE, correlated random effects estimator.

Table B8: Associations between ethnicity-based marriage customs and overweight (full model results for models without female interaction terms, panel D of Table 3.2)

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Marriage customs						
Patrilocality	0.017**		0.016**		0.005	-0.002
	(0.007)		(0.007)		(0.009)	(0.009)
Matrilocality	0.022***		0.024***		0.014	0.012
	(0.008)		(0.009)		(0.009)	(0.009)
Bridewealth		0.018***		0.021***	0.017**	0.025***
		(0.006)		(0.006)	(0.009)	(0.009)
Individual Characteristics						
Female	0.111***	0.105***	0.075***	0.075***	0.111***	0.075***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Age in year	0.038***	0.037***	0.039***	0.037***	0.038***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age in year squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling	0.003***	0.003***	-0.000	-0.001	0.003***	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Being married	0.068***	0.067***	0.029***	0.029***	0.068***	0.029***
	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.007)
Have work in the past week	-0.001	-0.001	0.008*	0.008*	-0.001	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Live in urban areas	0.058***	0.063***	0.020**	0.022***	0.058***	0.020**
	(0.005)	(0.005)	(0.008)	(0.008)	(0.005)	(0.008)
Religion: Islam	-0.032***	-0.043***	0.023	0.021	-0.035***	0.023
	(0.009)	(0.007)	(0.022)	(0.022)	(0.009)	(0.022)
History of smoking	-0.084***	-0.084***	-0.030***	-0.031***	-0.084***	-0.030***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)
Household characteristics						
Household size	0.004***	0.004***	0.000	0.001	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Real expenditure/capita	0.052***	0.053***	0.024***	0.025***	0.052***	0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Share of staple food expenditure	-0.034**	-0.030**	0.020	0.014	-0.033**	0.020
	(0.015)	(0.014)	(0.016)	(0.015)	(0.015)	(0.016)
Share of cooking oil expenditure	0.117**	0.120**	0.085	0.089	0.118**	0.085
	(0.057)	(0.054)	(0.062)	(0.060)	(0.057)	(0.062)
Share of meat/fish expenditure	-0.006	0.025	-0.038*	-0.030	-0.007	-0.037*
	(0.021)	(0.019)	(0.023)	(0.021)	(0.021)	(0.023)
Own TV/HH appliances	0.022***	0.022***	0.004	0.005	0.022***	0.004
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)

Share of food expenditure	-0.056***	-0.059***	-0.027**	-0.022*	-0.056***	-0.027**
	(0.012)	(0.011)	(0.013)	(0.012)	(0.012)	(0.013)
Community characteristics						
Garbage/manure exposure	-0.003	-0.005	0.004	0.003	-0.003	0.004
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Pop. density (pop/hasq)	0.005***	0.005***	0.001	0.001*	0.005***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Farmland share	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Clean water access	0.002	0.003	-0.001	-0.002	0.003	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Clean toilet access	0.014***	0.016***	0.009**	0.011***	0.014***	0.009**
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Electricity access	0.005	0.014	-0.010	-0.005	0.004	-0.010
	(0.010)	(0.009)	(0.012)	(0.011)	(0.010)	(0.012)
Car road available	0.002	0.000	0.002	0.001	0.002	0.002
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Health facility available	-0.013**	-0.011*	-0.020***	-0.021***	-0.013**	-0.020***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Time averages						
Mean years of schooling			0.003***	0.004***		0.003***
			(0.001)	(0.001)		(0.001)
Mean being married			0.086***	0.077***		0.087***
			(0.009)	(0.009)		(0.009)
Mean have worked in the past week			-0.031***	-0.027***		-0.030***
			(0.009)	(0.008)		(0.009)
Mean live in urban areas			0.015	0.024**		0.014
			(0.011)	(0.010)		(0.011)
Mean household size			0.006***	0.005***		0.006***
			(0.002)	(0.002)		(0.002)
Mean real expenditure/capita			0.061***	0.056***		0.061***
			(0.006)	(0.006)		(0.006)
Mean religion: Islam			-0.058**	-0.064***		-0.063**
			(0.024)	(0.023)		(0.025)
Mean history of smoking			-0.104***	-0.095***		-0.104***
			(0.011)	(0.010)		(0.011)
Mean share of staple food expenditure			-0.166***	-0.107***		-0.162***
			(0.040)	(0.034)		(0.040)
Mean share of cooking oil expenditure			0.283*	0.196		0.287*
			(0.161)	(0.139)		(0.161)

Mean share of meat/fish expenditure			0.210***	0.270***		0.201***
			(0.056)	(0.047)		(0.056)
Mean own TV/hh appliances			0.055***	0.043***		0.054***
			(0.012)	(0.011)		(0.012)
Mean share of food expenditure			-0.093***	-0.111***		-0.095***
			(0.029)	(0.025)		(0.029)
Mean garbage/manure exposure			-0.028***	-0.032***		-0.029***
			(0.008)	(0.007)		(0.008)
Mean pop. density (pop/hasq)			0.010***	0.008***		0.011***
			(0.002)	(0.002)		(0.002)
Mean farmland share			-0.000	-0.000		0.000
			(0.002)	(0.002)		(0.002)
Mean clean water access			0.004	0.012		0.008
			(0.009)	(0.008)		(0.009)
Mean clean toilet access			0.008	-0.001		0.008
			(0.009)	(0.008)		(0.009)
Mean electricity access			0.057*	0.059***		0.053*
			(0.030)	(0.023)		(0.030)
Mean car road available			-0.021	-0.021		-0.021
			(0.018)	(0.016)		(0.018)
Mean health facility available			0.056***	0.065***		0.058***
			(0.013)	(0.012)		(0.013)
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	0.371	0.365	0.371	0.365	0.371	0.371

Note: *** p<0.01, ** p<0.05, * p<0.10.

Table B9: Associations between ethnicity-based marriage customs and adult overweight (without consumption controls)

	RE		CRE		RE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Patrilocality	0.035***		0.031***		0.026**	0.012
	(0.009)		(0.009)		(0.012)	(0.012)
Matrilocality	0.006		0.006		-0.000	-0.006
	(0.012)		(0.012)		(0.013)	(0.013)
Bridewealth		0.021**		0.025***	0.013	0.026**
		(0.009)		(0.009)	(0.012)	(0.012)
Panel B: Women						
Patrilocality	-0.003		-0.005		-0.017	-0.026**
	(0.009)		(0.009)		(0.012)	(0.012)
Matrilocality	0.032***		0.037***		0.023*	0.022*
	(0.012)		(0.012)		(0.013)	(0.013)
Bridewealth		0.014		0.018**	0.02*	0.031***
		(0.009)		(0.009)	(0.012)	(0.012)
Panel C: Difference between women and men (female interaction term)						
Patrilocality	-0.039***		-0.036***		-0.043***	-0.039**
	(0.012)		(0.012)		(0.016)	(0.016)
Matrilocality	0.026		0.031*		0.023	0.028
	(0.016)		(0.016)		(0.018)	(0.018)
Bridewealth		-0.007		-0.007	0.007	0.005
		(0.012)		(0.012)	(0.017)	(0.017)
Panel D: Overall associations among adults (without including female interaction term)						
Patrilocality	0.015**		0.012*		0.003	-0.008
	(0.007)		(0.007)		(0.009)	(0.009)
Matrilocality	0.020**		0.023***		0.013	0.010
	(0.008)		(0.009)		(0.009)	(0.009)
Bridewealth		0.017***		0.021***	0.017**	0.029***
		(0.006)		(0.006)	(0.009)	(0.009)
Observations	65560	74329	65560	74325	65560	65560
Mean outcome	0.371	0.365	0.371	0.365	0.371	0.371

Note: *** p<0.01, ** p<0.05, * p<0.10.

Table B10: Associations between ethnicity-based marriage customs and adult BMI based on urban and rural residence

	RE (1)	(2)	CRE (3)	(4)	RE (5)	CRE (6)
Panel A: Males in rural areas						
Patrilocality	0.219**		0.232***		0.088	0.039
	(0.088)		(0.089)		(0.106)	(0.106)
Matrilocality	0.059		0.002		-0.028	-0.127
	(0.110)		(0.112)		(0.118)	(0.119)
Bridewealth		0.222**		0.214**	0.199*	0.299***
		(0.088)		(0.089)	(0.111)	(0.111)
Panel B: Males in urban areas						
Patrilocality	0.310***		0.253**		0.23*	0.117
	(0.103)		(0.103)		(0.135)	(0.133)
Matrilocality	0.064		0.152		0.019	0.074
	(0.126)		(0.126)		(0.14)	(0.139)
Bridewealth		0.111		0.164*	0.098	0.175
		(0.096)		(0.095)	(0.132)	(0.131)
Difference between urban-rural among patrilocal males (p-value)	0.437		0.858		0.325	0.581
Difference between urban-rural among matrilocal males (p-value)	0.972		0.285		0.757	0.182
Difference between urban-rural among bridewealth males (p-value)		0.347		0.673	0.501	0.399
Panel C: Females in rural areas						
Patrilocality	0.098		0.149		-0.046	-0.056
	(0.103)		(0.103)		(0.128)	(0.128)
Matrilocality	0.202		0.199		0.103	0.057
	(0.13)		(0.132)		(0.141)	(0.142)
Bridewealth		0.21**		0.231**	0.2	0.299**
		(0.101)		(0.101)	(0.13)	(0.131)
Panel D: Females in urban areas						
Patrilocality	-0.041		-0.075		-0.325**	-0.406***
	(0.112)		(0.112)		(0.141)	(0.141)
Matrilocality	0.236*		0.369***		0.062	0.165
	(0.13)		(0.131)		(0.145)	(0.146)
Bridewealth		0.194*		0.248**	0.409***	0.474***
		(0.103)		(0.103)	(0.137)	(0.137)
Difference between urban-rural among patrilocal females (p-value)	0.279		0.079		0.078	0.026
Difference between urban-rural among matrilocal females (p-value)	0.819		0.253		0.795	0.5

Difference between urban-rural among bridewealth females (p-value)		0.895		0.882	0.178	0.256
Difference between patrilocal males-females in rural areas (p-value)	0.346		0.511		0.398	0.542
Difference between matrilocal males-females in rural areas (p-value)	0.399		0.243		0.472	0.309
Difference between bridewealth males-females in rural areas (p-value)		0.928		0.898	0.999	0.999
Difference between patrilocal males-females in urban areas (p-value)	0.018		0.025		0.003	0.005
Difference between matrilocal males-females in urban areas (p-value)	0.342		0.223		0.832	0.644
Difference between bridewealth males-females in urban areas (p-value)		0.554		0.543	0.099	0.107
Observations	65551	74308	65551	74308	65551	65551
Mean outcome	22.412	22.35	22.412	22.35	22.412	22.412

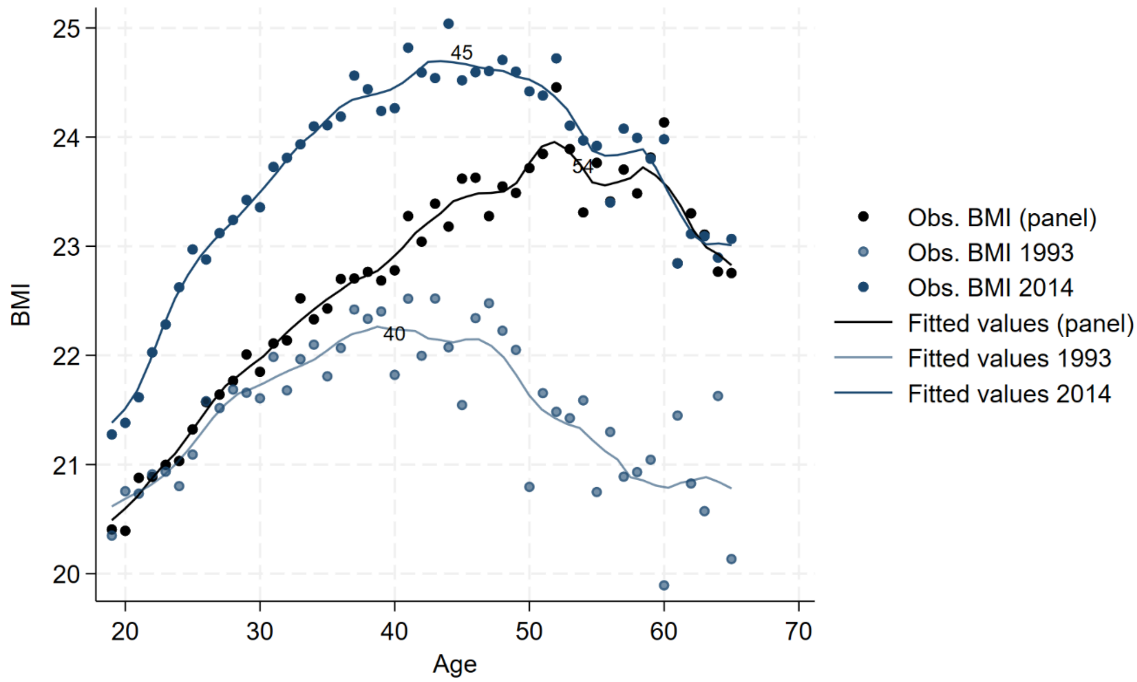
Note: *** p<0.01, ** p<0.05, * p<0.10.

Table B11: Associations between ethnicity-based marriage customs and adult BMI based on survey waves

	Separate regressions		Combined regressions			Separate regressions		Combined regressions	
	RE	CRE	RE	CRE		RE	CRE	RE	CRE
	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
Panel A: Patrilocality among males over time					*Panel D: Patrilocality among females over time*				
IFLS 1993	0.204**	0.180*	0.164	0.045	IFLS 1993	0.049	0.059	0.088	0.006
	(0.097)	(0.099)	(0.128)	(0.131)		(0.11)	(0.111)	(0.136)	(0.138)
IFLS 1997	0.230***	0.212**	0.22**	0.136	IFLS 1997	0.178*	0.175*	-0.055	-0.119
	(0.088)	(0.09)	(0.111)	(0.114)		(0.099)	(0.1)	(0.124)	(0.126)
IFLS 2000	0.277***	0.254***	0.24**	0.151	IFLS 2000	0.162*	0.183*	0.014	-0.039
	(0.083)	(0.084)	(0.103)	(0.105)		(0.098)	(0.099)	(0.12)	(0.122)
IFLS 2007	0.338***	0.296***	0.273**	0.189*	IFLS 2007	0.02	0.006	-0.103	-0.161
	(0.092)	(0.093)	(0.114)	(0.113)		(0.104)	(0.104)	(0.13)	(0.13)
IFLS 2014	0.279***	0.270***	0.102	0.066	IFLS 2014	-0.168	-0.156	-0.584***	-0.591***
	(0.101)	(0.1)	(0.127)	(0.125)		(0.118)	(0.118)	(0.146)	(0.145)
Panel B: Matrilocality among males over time					*Panel E: Matrilocality among females over time*				
IFLS 1993	-0.067	-0.005	-0.082	-0.086	IFLS 1993	0.357***	0.429***	0.389***	0.399***
	(0.120)	(0.122)	(0.140)	(0.141)		(0.127)	(0.129)	(0.141)	(0.143)
IFLS 1997	0.060	0.058	0.067	0.021	IFLS 1997	0.471***	0.494***	0.321**	0.303**
	(0.121)	(0.123)	(0.133)	(0.134)		(0.126)	(0.128)	(0.137)	(0.14)
IFLS 2000	0.134	0.174	0.121	0.115	IFLS 2000	0.358***	0.429***	0.259*	0.277**
	(0.105)	(0.107)	(0.116)	(0.117)		(0.122)	(0.124)	(0.135)	(0.137)
IFLS 2007	0.001	0.014	-0.036	-0.048	IFLS 2007	0.150	0.219	0.074	0.115
	(0.124)	(0.126)	(0.131)	(0.132)		(0.134)	(0.135)	(0.146)	(0.147)
IFLS 2014	0.100	0.102	-0.017	-0.027	IFLS 2014	0.025	0.068	-0.264	-0.231
	(0.14)	(0.139)	(0.152)	(0.151)		(0.15)	(0.151)	(0.164)	(0.165)
Panel C: Bridewealth among males over time					*Panel F: Bridewealth among females over time*				
IFLS 1993	0.078	0.159	0.035	0.185	IFLS 1993	-0.034	0.054	-0.098	0.044
	(0.097)	(0.098)	(0.138)	(0.141)		(0.104)	(0.105)	(0.136)	(0.139)
IFLS 1997	0.083	0.12	-0.012	0.087	IFLS 1997	0.335***	0.377***	0.344***	0.435***
	(0.086)	(0.087)	(0.116)	(0.118)		(0.097)	(0.097)	(0.127)	(0.129)
IFLS 2000	0.146*	0.190**	0.031	0.132	IFLS 2000	0.224**	0.303***	0.209*	0.321**
	(0.08)	(0.081)	(0.106)	(0.107)		(0.095)	(0.096)	(0.124)	(0.125)
IFLS 2007	0.214**	0.208**	0.082	0.141	IFLS 2007	0.086	0.107	0.172	0.233*
	(0.093)	(0.093)	(0.119)	(0.118)		(0.102)	(0.103)	(0.134)	(0.134)
IFLS 2014	0.308***	0.312***	0.274**	0.306**	IFLS 2014	0.244**	0.258**	0.666***	0.686***
	(0.102)	(0.101)	(0.133)	(0.132)		(0.116)	(0.116)	(0.151)	(0.151)

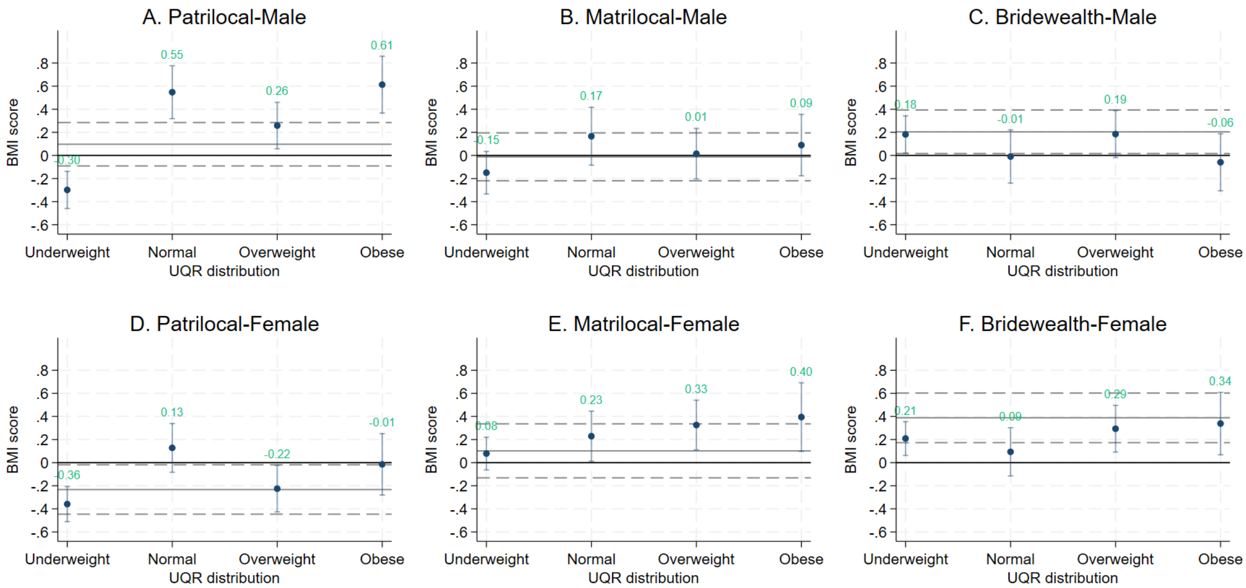
Note: *** p<0.01, ** p<0.05, * p<0.10. In the ‘separate regression’ columns, the associations of locality customs and bridewealth were estimated separately. In the ‘combined regression’ columns, the associations of locality customs and bridewealth were estimated in the same regressions to control for overlapping practices.

Figure B1: Associations between BMI and age



Note: Polynomial plotting of BMI and age among cross-sectional and panel IFLS adult samples. There were 11,841 adults in IFLS 1993, 27,464 adults in IFLS 2014, and 5,290 adults who were present in all five survey waves. Age at the peak of the curve is calculated using a simple quadratic polynomial regression model.

Figure B2: Associations between marriage customs and BMI by nutrition status (all marriage customs included in the same regressions)



Notes: Results from unconditional quantile regressions with correlated random effects (CRE). Patrilocal, matrilocal, and bridewealth customs were jointly included in the same regressions. Point estimates with 95 % confidence intervals are shown. For comparison, the horizontal straight lines indicate the average CRE results from Table 3.1 (dashed lines above and below are 95 % confidence intervals).

Appendix C

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

Table C1 Number of districts serviced by digital platforms by year

Entry year	(1) Have either Gojek or Grab	(2) Have Gojek	(3) Have Grab	(4) Have Gojek only	(5) Have Grab only	(6) Have both Gojek and Grab	(7) Have no Gojek or Grab
2015	34	34	32	2	0	32	463
2016	13	12	11	2	1	10	450
2017	91	61	85	6	30	55	359
2018 (Jan-Mar)	20	0	20	0	20	0	339
Total	158	107	148	10	51	97	339

Note: Column (1) shows the number of districts serviced by either Gojek or Grab. Column (2) shows the number of districts serviced by Gojek (some of these may also be covered by Grab). Column (3) shows the number of districts serviced by Grab (some of these may also be covered by Gojek). Column (4) shows the number of districts serviced only by Gojek. Column (5) shows the number of districts serviced only by Grab. Column (6) shows the number of districts serviced by both Gojek and Grab. Column (7) shows the number of districts not serviced by either platform.

Table C2 Descriptive statistics of nutritional status and district characteristics

	2013				2018			
Control districts *Nutritional outcomes*	Mean	SD	Min	Max	Mean	SD	Min	Max
% overweight (Asia)	0.46	0.50	0	1	0.53	0.50	0	1
% overweight (WHO)	0.27	0.44	0	1	0.35	0.48	0	1
% obese (Asia)	0.15	0.36	0	1	0.22	0.41	0	1
% obese (WHO)	0.06	0.23	0	1	0.09	0.29	0	1
% underweight	0.09	0.29	0	1	0.08	0.27	0	1
% central obesity (Asia)	0.29	0.45	0	1	0.34	0.47	0	1
% central obesity (WHO)	0.19	0.39	0	1	0.24	0.43	0	1
District characteristics								
% population with internet	0.08	0.06	0.00	0.34	0.08	0.06	0.00	0.34
GDP per capita (log)	16.85	0.65	14.80	19.67	16.86	0.64	14.80	19.67
Regional gas price	8.54	0.23	8.10	10.41	8.53	0.21	8.10	10.41
% population with senior high degree and above	0.29	0.12	0.02	0.68	0.29	0.12	0.02	0.68
% population in urban areas	0.29	0.25	0.00	1.00	0.29	0.25	0.00	1.00
% population with employment	0.52	0.08	0.33	0.75	0.52	0.08	0.33	0.75
% household with toilets	0.59	0.20	0.00	0.98	0.60	0.20	0.00	0.98
Population age	37.32	2.36	31.02	44.12	37.42	2.34	31.02	44.12
% household with clean water	0.37	0.21	0.00	0.99	0.38	0.21	0.00	0.99
Gender Ratio (Male/Female)	0.97	0.06	0.78	1.15	0.98	0.05	0.78	1.15
% population with health insurance	0.45	0.22	0.00	0.98	0.46	0.22	0.00	0.98
Number of store at the village level	2.89	1.93	0.00	11.66	2.92	1.93	0.00	11.66
Number of health centers at the village level	0.07	0.05	0.01	0.62	0.07	0.05	0.01	0.62
Number of hospitals at the village level	0.01	0.01	0.00	0.12	0.01	0.01	0.00	0.12
Individual characteristics								
% residence in urban areas	0.38	0.48	0	1	0.33	0.47	0	1
% female	0.52	0.50	0	1	0.52	0.50	0	1
Age	39.68	12.16	19	65	40.21	12.28	19	65
% education above junior high	0.50	0.50	0	1	0.55	0.50	0	1
% in employment	0.26	0.44	0	1	0.25	0.43	0	1
Wealth quantile	2.75	1.45	1	5	2.98	1.38	1	5

Treatment districts *Nutritional outcomes*	2013 Mean	SD	Min	Max	2018 Mean	SD	Min	Max
% overweight (Asia)	0.50	0.50	0	1	0.58	0.49	0	1
% overweight (WHO)	0.31	0.46	0	1	0.40	0.49	0	1
% obese (Asia)	0.18	0.39	0	1	0.26	0.44	0	1
% obese (WHO)	0.07	0.26	0	1	0.12	0.32	0	1
% underweight	0.09	0.29	0	1	0.08	0.27	0	1
% central obesity (Asia)	0.33	0.47	0	1	0.39	0.49	0	1
% central obesity (WHO)	0.22	0.42	0	1	0.28	0.45	0	1
District characteristics								
% population with internet	0.18	0.10	0.02	0.43	0.18	0.10	0.02	0.43
GDP per capita (log)	17.12	0.69	16.08	19.61	17.10	0.70	16.08	19.61
Regional gas price	8.40	0.07	8.17	8.58	8.40	0.07	8.17	8.58
% population with senior high degree and above	0.39	0.18	0.09	0.78	0.38	0.17	0.09	0.78
% population in urban areas	0.70	0.30	0.09	1.00	0.68	0.30	0.09	1.00
% population with employment	0.52	0.06	0.35	0.68	0.52	0.06	0.35	0.68
% household with toilets	0.73	0.19	0.13	0.98	0.73	0.19	0.13	0.98
Population age	37.96	2.39	31.99	45.42	38.09	2.40	31.99	45.42
% household with clean water	0.53	0.27	0.11	1.00	0.52	0.27	0.11	1.00
Gender Ratio (Male/Female)	1.00	0.04	0.90	1.11	1.00	0.04	0.90	1.11
% population with health insurance	0.46	0.15	0.11	0.92	0.46	0.15	0.11	0.92
Number of store at the village level	3.62	1.93	0.64	10.56	3.62	1.92	0.64	10.56
Number of health centers at the village level	0.03	0.01	0.01	0.07	0.03	0.01	0.01	0.07
Number of hospitals at the village level	0.01	0.01	0.00	0.06	0.01	0.01	0.00	0.06
Individual characteristics								
% residence in urban areas	0.69	0.46	0	1	0.71	0.45	0	1
% female	0.53	0.50	0	1	0.53	0.50	0	1
Age	40.44	12.43	19	65	40.66	12.69	19	65
% education above junior high	0.58	0.49	0	1	0.64	0.48	0	1
% in employment	0.36	0.48	0	1	0.37	0.48	0	1
Wealth quantile	3.30	1.37	1	5	3.27	1.41	1	5

Note: Calculated using Riskesdas 2013 and 2018 data.

Table C3 Additional analysis using Asian cutoff

Heterogeneity	N (T; C)	Overweight	Obesity	Central obesity
All sample	T: 158	0.012	0.004	0.009
	C: 339	(0.009)	(0.007)	(0.014)
Cities	T: 65	0.056***	0.017	0.041***
	C: 33	(0.014)	(0.014)	(0.015)
Regencies	T: 93	0.009	-0.001	-0.004
	C: 306	(0.007)	(0.01)	(0.018)
GDP above median	T: 136	0.013	0.004	0.01
	C: 113	(0.01)	(0.006)	(0.013)
GDP below median	T: 22	-0.003	0.011	-0.027
	C: 226	(0.016)	(0.015)	(0.02)
With food delivery	T: 41	0.059***	0.015	0.084***
	C: 339	(0.018)	(0.015)	(0.032)
Without food delivery	T: 117	0.005	0.003	-0.003
	C: 339	(0.007)	(0.007)	(0.012)
Excl. metropolitan	T: 155	0.011	0.004	0.007
	C: 339	(0.009)	(0.006)	(0.013)
Excl. early adopters	T: 137	0.008	0.003	0.002
	C: 339	(0.008)	(0.006)	(0.013)

Note: *** p<0.01, ** p<0.05, * p<0.10. 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. Estimated using the 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. N is number of districts, T is treatment districts, C is control districts.

Table C4 Parallel trends of heterogeneous treatment effects of super apps on BMI, waist circumference, and nutritional status

Heterogeneity	N (T; C)	BMI	Waist circum-ference	Overweight (W)	Obesity (W)	Central obesity (W)	Overweight (A)	Obesity (A)	Central obesity (A)	Under-weight
All sample	T: 152	-0.139	-0.114	-0.017	-0.009	-0.007	-0.015	-0.018	-0.009	-0.004
	C: 288	(0.105)	(0.56)	(0.014)	(0.007)	(0.014)	(0.011)	(0.014)	(0.017)	(0.006)
Cities	T: 62	-0.644**	-1.755**	-0.089***	-0.047***	-0.054**	-0.056**	-0.1***	-0.086***	-0.026***
	C: 29	(0.268)	(0.811)	(0.034)	(0.015)	(0.022)	(0.026)	(0.031)	(0.027)	(0.009)
Regencies	T: 90	0.013	0.645	0.005	0.004	0.013	-0.001	0.009	0.017	0.007
	C: 259	(0.086)	(0.694)	(0.012)	(0.008)	(0.01)	(0.008)	(0.014)	(0.011)	(0.008)
GDP above median	T: 130	-0.063	0.326	-0.006	-0.005	0.002	-0.008	-0.011	0.001	-0.004
	C: 100	(0.103)	(0.46)	(0.015)	(0.007)	(0.013)	(0.012)	(0.016)	(0.016)	(0.007)
GDP below median	T: 22	-0.087	0.056	-0.022**	-0.004	0.002	-0.017	-0.018**	0.002	-0.008
	C: 188	(0.111)	(0.505)	(0.011)	(0.006)	(0.011)	(0.014)	(0.009)	(0.013)	(0.007)
With food delivery	T: 39	-0.522**	-3.051***	-0.073**	-0.04**	-0.076**	-0.05**	-0.085**	-0.101***	-0.029**
	C: 288	(0.237)	(0.813)	(0.031)	(0.018)	(0.031)	(0.021)	(0.036)	(0.036)	(0.012)
Without food delivery	T: 113	-0.093	0.45	-0.011	-0.006	0.002	-0.01	-0.01	0.004	-0.001
	C: 288	(0.083)	(0.406)	(0.011)	(0.004)	(0.009)	(0.009)	(0.008)	(0.011)	(0.006)
Excl. metropolitan	T: 149	-0.128	-0.006	-0.016	-0.008	-0.005	-0.014	-0.016	-0.006	-0.003
	C: 288	(0.099)	(0.532)	(0.013)	(0.007)	(0.013)	(0.01)	(0.013)	(0.016)	(0.006)
Excl. early adopters	T: 133	-0.113	0.18	-0.014	-0.007	-0.001	-0.013	-0.013	-0.001	-0.002
	C: 288	(0.1)	(0.48)	(0.013)	(0.006)	(0.012)	(0.01)	(0.012)	(0.015)	(0.006)

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas) 2007 and 2013 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. N is number of districts, T is treatment districts, C is control districts.

Table C5 Spillover effects of super apps on nutritional outcomes: Incorporating neighborhood influences

	N (T; C)	BMI	Waist circum-ference	Overweight (W)	Obesity (W)	Central obesity (W)	Overweight (A)	Obesity (A)	Central obesity (A)	Under-weight
Parallel trend										
Distance lag 25 km	T: 158 C: 288	-0.176 (0.128)	-0.111 (0.682)	-0.02 (0.017)	-0.013 (0.008)	-0.012 (0.015)	-0.016 (0.013)	-0.023 (0.017)	-0.012 (0.021)	-0.005 (0.007)
Distance lag 50 km	T: 133 C: 288	-0.232 (0.143)	0.26 (0.503)	-0.025** (0.012)	-0.009 (0.006)	-0.005 (0.008)	-0.026** (0.012)	-0.014* (0.008)	-0.006 (0.011)	0.007 (0.009)
Excl. distance lag 25 km	T: 157 C: 283	-0.198 (0.138)	0.027 (0.711)	-0.021 (0.018)	-0.013 (0.008)	-0.01 (0.015)	-0.018 (0.015)	-0.023 (0.017)	-0.01 (0.02)	-0.002 (0.008)
Excl. distance lag 50 km	T: 176 C: 264	-0.637*** (0.109)	1.457*** (0.506)	-0.057*** (0.011)	-0.026*** (0.004)	0.004 (0.01)	-0.056*** (0.012)	-0.036*** (0.007)	0.01 (0.013)	0.033*** (0.008)
Spillover check										
Distance lag 25 km	T: 158 C: 339	0.186* (0.109)	0.525 (0.555)	0.015 (0.01)	0.009* (0.006)	0.011 (0.011)	0.014 (0.011)	0.004 (0.006)	0.012 (0.014)	-0.009 (0.006)
Distance lag 50 km	T: 158 C: 339	0.186** (0.088)	0.227 (0.392)	0.023** (0.009)	0.013*** (0.005)	0.009 (0.01)	0.015* (0.008)	0.014** (0.007)	0.013 (0.012)	-0.002 (0.005)
Excl. distance lag 25 km	T: 158 C: 325	0.209* (0.111)	0.489 (0.556)	0.018 (0.011)	0.011* (0.006)	0.01 (0.011)	0.017 (0.011)	0.005 (0.007)	0.012 (0.014)	-0.009* (0.006)
Excl. distance lag 50 km	T: 158 C: 282	0.38*** (0.081)	0.17 (0.369)	0.043*** (0.01)	0.029*** (0.004)	0.002 (0.01)	0.034*** (0.011)	0.018*** (0.007)	0.013 (0.013)	-0.016*** (0.005)

Note: *** p<0.01, ** p<0.05, * p<0.10. Variables are aggregated at the district level from the Basic Health Survey (Riskesdas). Parallel trend analysis uses Riskesdas 2007 and 2013. Spillover check analysis uses 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. N is number of districts, T is treatment districts, C is control districts.

Table C6 The effects of super apps on BMI and nutritional status: Heterogeneity analysis using individual characteristics

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

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 C7 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 C8 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

Notes: *** 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 - 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

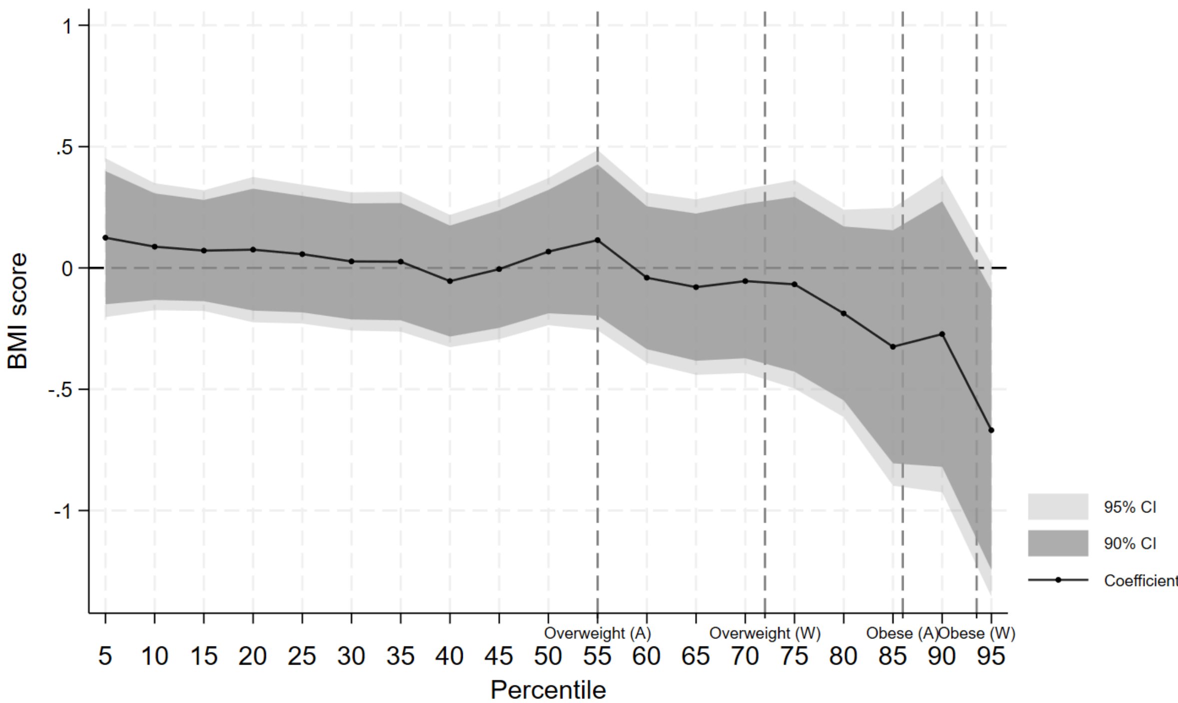
Table C9 Heterogeneous Effect Analysis of super apps weekly food expenditure and macronutrient

Outcome	Quantile 1		Quantile 2		Quantile 3		Quantile 4		Quantile 5	
	Mean	Coefficient	Mean	Coefficient	Mean	Coefficient	Mean	Coefficient	Mean	Coefficient
Per capita expenditure (log)	12.46	.015	12.90	.005	13.24	.003	13.61	0	14.34	.085***
		(.018)		(.005)		(.003)		(.004)		(.019)
Per capita food expenditure (log)	12.01	.041	12.40	.022	12.68	.04*	12.96	.011	13.38	.055
		(.032)		(.014)		(.022)		(.021)		(.039)
Per capita expenditure (real)	263,133	3275.061	403,281	2721.516	568,900	2052.779	828,525	-129.014	1,924,143	202425.9***
		(4681.871)		(2079.843)		(2100.501)		(3324.681)		(39507.69)
Per capita food expenditure (real)	169,263	6632.08	248,715	6787.319*	330,932	13581.3**	441,554	7677.951	698,610	38305.4
		(5126.642)		(3569.395)		(6928.229)		(8814.333)		(26034.12)
Per capita calories (kcal)	1667.69	17.374	1918.93	-6.858	2079.35	41.115	2241.77	9.797	2415.19	40.529
		(32.242)		(27.57)		(31.816)		(36.192)		(51.224)
Per capita carbohydrate (gram)	267.06	3.245	295.52	.635	311.70	8.355	326.64	.938	335.62	6.102
		(7.167)		(5.403)		(6.471)		(6.919)		(8.152)
Per capita fat (gram)	36.46	1.377	45.76	.845	52.24	2.051*	59.24	2.27	68.62	1.816
		(1.103)		(1.085)		(1.15)		(1.642)		(2.312)
Per capita protein (gram)	44.78	1.012	53.40	.481	59.59	.842	66.57	1.029	77.66	2.406
		(1.006)		(.956)		(1.095)		(1.501)		(2.498)
Expenditure of rice	46,304	-1,911.658	49,306	87.646	52,619	2,305.977	54,737	-741.482	52,648	-841.906
		(2,227.32)		(2,230.409)		(3,003.83)		(4,130.03)		(5,017.88)
Expenditure of fish	10,749	2,847.915	17,489	386.749	23,755	1,044.708	31,581	98.306	44,440	1,303.668
		(1,979.12)		(1,898.22)		(2,550.57)		(3,468.5)		(5,819.9)
Expenditure of meat	12,943	1,144.989	21,611	2,813.877	31,677	1,769.179	46,305	-342.419	79,282	8,071.272
		(907.442)		(1,856.174)		(1,961.4)		(2,612.66)		(5,478.95)
Expenditure of legumes	8,008	-407.249	9,300	295.61	10,348	1,023.012	10,987	715.625	11,011	547.538
		(459.961)		(490.149)		(672.724)		(605.577)		(702.289)
Expenditure of vegetable	17,631	175.896	22,665	-46.816	26,963	640.556	30,985	272.989	34,799	198.545
		(798.274)		(1,297.06)		(1,709.62)		(2,187.06)		(3,467.185)
Expenditure of fruit	5,671	1,443.559	9,686	2,399.06**	14,179	1,994.5**	21,190	3,262.66**	37,866	8,060.837**

		(913.933)		(1,219.331)		(996.527)		(1,501.08)		(3,388.068)
Expenditure of sugar	8,687	-338.953	10,634	-264.734	12,337	-36.491	13,888	-237.832	14,894	-2,634.62**
		(737.885)		(543.641)		(654.736)		(738.484)		(1,184.108)
Expenditure of oil	8,118	28.065	9,780	194.525	10,827	428.066	11,933	-341.243	12,752	-994.592
		(337.024)		(496.901)		(616.806)		(640.171)		(768.181)
Expenditure of prepared food	44,581	4,078.813	71,916	3,117.75	98,790	5,371.452	136,780	5,684.296	226,154	17,405.3
		(4,179.608)		(3,322.581)		(4,714.75)		(6,268.5)		(13,051.56)
Expenditure of cigarette	21,237	2,193.467*	35,285	503.658	45,901	2,953.631	55,118	846.302	55,790	-9,590.719**
		(1,284.905)		(2,784.996)		(2,975.5)		(3,742.18)		(4,069.843)

Notes: *** 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 2012-2019 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

Figure C1 Pre-trend test of super apps' effects across BMI distribution



Note: Coefficients with 95% and 90% confidence intervals are shown. RIF-regression of individual-level data, estimated using the inverse probability weighting (IPW) method. Riskesdas 2013 and 2018 are used for this analysis. The overweight and obesity cutoff was determined using the Asian (A) and the 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.