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Impacts of Supermarkets on Food Consumers and Producers in China

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Abstract

Supermarkets are expanding rapidly in low- and middle-income countries. Compared to traditional food markets, supermarkets are larger, more integrated, and more efficient in procurement and sales. Hence, supermarkets have a more powerful influence on all actors along agri-food value chains. A key question is whether supermarkets are inclusive and beneficial to disadvantaged groups of consumers and producers. This dissertation addresses this knowledge gap through examining the impact of supermarkets on children, women, and smallholder farmers using panel data from China and econometric difference-in-differences techniques.

For consumers, increased supermarket access can improve nutrition. Chapter 2 shows that the nearby establishment of a supermarket increase dietary diversity and nutrient intake among children, with effects being particularly strong in rural areas and low-income households. The key mechanism is that supermarkets improve the availability and affordability of diverse foods. Notably, supermarkets also increase children’s height-for-age, a marker of better long-term nutrition, without increasing weight-for-age or the risk of overweight and obesity.

For women, the expansion of supermarkets alleviates the burden of unpaid work associated with gender-based social norms. Chapter 3 demonstrates that supermarkets offer convenient one-stop shopping and a wide variety of foods, which significantly reduces the time women spend on shopping and cooking. Importantly, these time savings are achieved without harming household dietary quality. In fact, we find positive nutritional effects on those with lower dietary quality. Such time savings also empower women through increasing their participation in paid employment, contributing to greater gender equality.

Supermarket expansion also affects smallholder farmers, though in nuanced ways. Chapter 4 finds positive income effects for remote grain farmers but neutral effects for peri-urban grain farmers. Specifically, supermarkets expand market access for remote farmers, leading to higher farm-gate prices and increased commercialization. Remote farmers also allocate more resources (i.e., land, labor, and purchased inputs) to grain production and finally earn higher income. Meanwhile, peri-urban farmers experience price declines and reduced commercialization due to intensified market competition. However, they adapt by shifting resources to off-farm work to maintain household income.

Overall, the key takeaway of this dissertation is that supermarket-led modernization of agri-food value chains fosters inclusive growth in the context of China: it uplifts disadvantaged consumers and producers without significant negative impacts on nutrition or welfare among other groups.

Zusammenfassung

Supermärkte expandieren in Entwicklungsländern rapide. Im Vergleich zu traditionellen Lebensmittelmärkten sind sie größer, stärker integriert und effizienter im Einkauf und in der Vermarktung. Daher haben sie einen stärkeren Einfluss auf alle Akteure entlang der agrarischen Wertschöpfungsketten. Eine zentrale Frage ist, ob Supermärkte inklusiv wirken und benachteiligten Konsumenten und Produzenten zugutekommen. Diese Dissertation adressiert diese Frage. Konkret werden die Auswirkungen von Supermärkten auf Kinder, Frauen und Kleinbauern mithilfe von Paneldaten aus China und ökonometrischen „Difference-in-Differences" Ansätzen untersucht.

Für Konsumenten, insbesondere Kinder, verbessert ein erhöhter Zugang zu Supermärkten die Ernährung. Kapitel 2 zeigt, dass die Eröffnung von Supermärkten im lokalen Kontext zu einer höheren Ernährungsvielfalt und einer verbesserten Nährstoffaufnahme bei Kindern führt, wobei die positiven Effekte in ländlichen Gebieten und einkommensschwachen Haushalten besonders ausgeprägt sind. Der zentrale Mechanismus besteht darin, dass Supermärkte die Verfügbarkeit und Erschwinglichkeit vielfältiger Lebensmittel verbessern. Bemerkenswert ist zudem, dass Supermärkte das lineare Größenwachstum der Kinder fördern – ein Indikator für verbesserte langfristige Ernährung –, ohne dabei das Risiko von Übergewicht und Adipositas zu erhöhen.

Für Frauen reduziert die Expansion von Supermärkten die Belastung durch unbezahlte Arbeit im Haushalt, die aus geschlechtsspezifischen sozialen Normen resultiert. Kapitel 3 zeigt, dass Supermärkte mit ihrem bequemen "One-Stop-Shopping"-Angebot und ihrer großen Auswahl an Lebensmitteln die Zeit, die Frauen für Einkäufe und Kochen aufwenden müssen, erheblich verringern. Wichtig dabei ist, dass diese Zeitersparnis nicht zu einer Verschlechterung der Ernährungsqualität im Haushalt führt. Vielmehr finden wir positive Ernährungseffekte bei Haushalten, deren Ernährungsqualität zuvor niedrig war. Die eingesparte Zeit stärkt zudem die Position der Frauen, indem sie ihre Teilhabe an bezahlter Beschäftigung erhöht und somit zur Geschlechtergleichstellung beiträgt.

Die Supermarktexpansion wirkt sich auch auf Kleinbauern aus, jedoch auf differenzierte Weise. Kapitel 4 zeigt positive Einkommenseffekte für Getreidebauern in abgelegenen Gebieten, während periurbane Getreidebauern keine wesentlichen Einkommensänderungen erfahren. Supermärkte erweitern den Marktzugang für abgelegene Bauern, was zu höheren Ab-Hof-Preisen und einer verstärkten Kommerzialisierung führt. Ferner investieren abgelegene Bauern mehr Ressourcen (Land, Arbeit und zugekaufte Betriebsmittel) in den Getreideanbau und erzielen dadurch höhere Einkommen. Periurbane Bauern hingegen erleben Preisrückgänge und eine reduzierte Kommerzialisierung aufgrund verstärkten Wettbewerbs am Markt. Sie passen sich jedoch an, indem sie Ressourcen stärker in außerlandwirtschaftliche Tätigkeiten verlagern, um das Haushaltseinkommen aufrechtzuerhalten.

Zusammenfassend lässt sich festhalten, dass die durch Supermärkte vorangetriebene Modernisierung der agrarischen Wertschöpfungsketten inklusives Wachstum fördert: Sie verbessert die Lage benachteiligter Konsumenten und Produzenten, ohne nennenswerte negative Auswirkungen auf Ernährung oder Wohlbefinden anderer Gruppen hervorzurufen.

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Reflecting on my PhD journey that began during the COVID-19 pandemic in 2021, I am reminded of the profound impact of this global crisis. Human society may face more risks and challenges in the future, underscoring the relevance of development research, which I have committed to pursue as my life’s career. May we all strive for and achieve a better future.

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List of Abbreviations

ATT	Average Treatment Effect on the Treated
BAZ	BMI-for-Age Z-score
BMI	Body Mass Index
CCFGP	Chinese Children's Food Guide Pagoda
CDDS	Child Dietary Diversity Score
CFCT	Chinese Food Composition Table
CFPS	Chinese Food Pagoda Score (Chapter 3)
CFPS	China Family Panel Studies (Chapter 4)
CHNS	China Health and Nutrition Survey
CNS	Chinese Nutrition Society
CPI	Consumer Price Index
DDS	Dietary Diversity Score
DID	Difference-in-Differences
DNDS	Dietary Nutrition Density Score
FAO	Food and Agriculture Organization of the United Nations
FDI	Foreign Direct Investment
FE	Fixed Effects
GDP	Gross Domestic Product
HAZ	Height-for-Age Z-score
LMICs	Low- and Middle-Income Countries
NBSC	National Bureau of Statistics of China
NDCPA	National Disease Control and Prevention Administration
NI	Nutrition Index
RUI	Relative Urbanicity Index
SDGs	Sustainable Development Goals
UI	Urbanicity Index
UN	United Nations
UNICEF	United Nations Children's Fund
USD	United States Dollar
WAZ	Weight-for-Age Z-score
WHO	World Health Organization
WTO	World Trade Organization
Yuan	Chinese Yuan

CHAPTER 1

General Introduction

"*Leave no one behind*" is the core commitment of the global community in the 2030 Agenda for Sustainable Development. Supporting children, women, and smallholder farmers – among the most vulnerable groups – is central to this mission, especially in relation to achieving several Sustainable Development Goals (SDGs), including SDG1 (No Poverty), SDG2 (Zero Hunger), SDG3 (Good Health and Well-being), SDG5 (Gender Equality), SDG8 (Decent Work and Economic Growth), and SDG12 (Responsible Consumption and Production). Yet progress has stalled. These groups increasingly face challenges of malnutrition, disempowerment, and poverty due to factors such as pandemics, climate change, economic volatility, and geopolitical tensions (UN, 2024). Addressing these challenges requires systemic strategies, as they are deeply interdependent and often rooted in enduring social norms and behaviors.

This dissertation consists of three studies that demonstrate how modernizing the food retail sector can be an interesting part of the solution, using data from China. Specifically, these studies focus on supermarkets, which are expanding rapidly in many low- and middle-income countries (LMICs), and their impact on child nutrition, women's empowerment, and smallholder farmers' incomes. The role of public policy in supporting sustainable outcomes is also discussed. The following section details the challenges faced by children, women, and smallholder farmers, and explores the nexus between them. Section 1.2 reviews the characteristics of supermarkets, summarizes the existing literature on their impacts, and identifies key knowledge gaps. Section 1.3 presents the context of China in which this dissertation is situated. Section 1.4 states the main research objectives and outlines the structure of the remainder of the dissertation.

1.1 Challenges of children, women, and smallholder farmers

Child malnutrition, largely caused by unbalanced diets, has profound consequences for physical growth, cognitive development, and human capital accumulation (Alderman & Fernald, 2017; Hoddinott et al., 2013). The prevalence of child underweight, associated with inadequate energy intake, has declined significantly over the past two decades, but the decline in protein and micronutrient (i.e., vitamins and minerals) deficiencies has been much slower (FAO et al., 2024). For instance, nearly half of the children in LMICs are deficient in vitamin A and zinc (Victora et al., 2021). Meanwhile, overweight and obesity are on the rise, primarily due to excessive consumption of energy-dense, highly processed foods (Popkin et al., 2020; Yuan et al., 2024). This dual burden of malnutrition is particularly persistent in low-income communities, where access to nutritious, fresh food is limited or unaffordable (Bai et al., 2021; Gebremichael et al., 2025). As more than one-third of LMICs now face both undernutrition and overnutrition (Hawkes et al., 2020), innovative strategies are needed to address both challenges without worsening either.

Gender inequality in time use significantly contributes to women's disempowerment. Globally, women perform an estimated 2.5 times more hours of unpaid household labor per day than men, restricting their opportunities for education, paid employment, and leisure (Dinkelman & Ngai, 2022; UN, 2024). Among these responsibilities, food provisioning tasks including shopping and cooking are particularly time-intensive. In many LMICs, tasks related to meal preparation account for over 30% of women's household chores (Ferrant et al., 2014; Singh & Pattanaik, 2020). Reducing time spent on these tasks is critical for promoting gender equity, but raises concerns about dietary outcomes. Studies show that more time spent on food preparation is often associated with fresher, more diverse meals (e.g., Monsivais et al., 2014). Reducing this time may lead women to simplify meals or rely on convenient but less nutritious foods, with negative implications for their own health and that of their families. Therefore, the key challenge is to alleviate women's time burdens in a way that sustains, rather than compromises, dietary quality and nutrition.

Smallholder farmers remain essential to food security in many LMICs. In Asia and sub-Saharan Africa, they manage about 80% of farmland and provide up to 80% of the food supply (Lowder et al., 2021). Yet paradoxically, they experience the highest rates of poverty and food insecurity (FAO, 2008). Agricultural policies have long aimed to increase smallholder productivity and income. Traditionally, smallholders relied on intensive family labor to sustain yields. However, the expansion of mechanization, chemical inputs, and modern production services is gradually eroding this advantage relative to larger farms (Ma & Sexton, 2021). Limited access to markets poses an additional challenge. In the absence of direct links to processors or retailers, many smallholders depend on intermediaries, whose imperfect market information creates high uncertainty about market demand and prices. For grain producers, this problem is especially prevalent, because the bulky nature of raw grain makes transport costs high relative to product value, further restricting sales opportunities (Barrett, 2008; Ma et al., 2024). More policy and research attention is therefore needed to improve market infrastructure and linkages as well as to increase productivity.

It is noteworthy that the above-mentioned challenges are closely interrelated and often have an intergenerational impact. Poor child nutrition not only limits health and cognitive development but also constrains future employment opportunities (Hoddinott et al., 2013). For girls, these constraints can entrench social norms that assign them early to unpaid household labor. In some settings, girls already spend more time on household chores than boys (UNICEF, 2016). In turn, women's unequal time burdens perpetuate gender inequalities in nutrition and education. At the household level, low farm income may lead to less expenditure on diverse and nutritious diets, thereby undermining child nutrition. These interdependent challenges contribute to long-term cycles of poverty, gender inequality, and nutrition insecurity.

1.2 The economics of supermarkets

Many LMICs are undergoing a rapid expansion of supermarkets and other large modern retailers, often referred to as the "supermarket revolution" or "supermarketization" (Nair, 2020). This transformation is often driven by globalization and foreign direct investment (FDI), and further accelerated by growing domestic food demand and investment (Qaim, 2017; Reardon et al., 2003). In regions such as Asia, supermarkets have diffused beyond cities into towns and villages, gaining substantial market share in food retailing (Reardon et al., 2012). More than retail outlets, supermarkets influence production, procurement, and consumption decisions across the entire farm-to-fork spectrum (Barrett et al., 2022).

For consumers, supermarkets reshape food environments and influence consumer choices. Compare to traditional food markets such as wet markets and street vendors , supermarkets offer a wider range of different food choices, more convenient shopping (e.g., longer operating hours), and lower prices for certain items due to economies of scale (Liu et al., 2024). These features may improve household access to diverse foods and improve dietary diversity, which is a prerequisite for balanced and adequate nutrition. Supermarket also sell labor-saving products, including processed or prepared foods, that can reduce women's time spent on cooking. Additionally, through offering a wide range of fresh and packaged foods under one roof (Lu & Reardon, 2018), supermarkets enable bulk shopping and reduce the frequency of shopping. These characteristics suggest that supermarkets could simultaneously support child nutrition and alleviate women's time burdens, which is an intersection underexplored in previous research.

However, these benefits are not without risks. Supermarkets also promote highly processed foods that are visually appealing and palatable but nutritionally inferior. Increased consumption of such products can displace healthier options, reducing micronutrient intake and increasing exposure to added sugars, fats, and salt. Some evidence already suggests that shopping in supermarkets is correlated with higher risks of obesity and other diet-related non-communicable diseases (Demmler et al., 2017; Otterbach et al., 2021). The dietary and health implications of supermarkets are likely shaped by consumer preferences, dietary culture, and income. However, most existing studies focus on urban African populations, with limited generalizability to children in other geographic and socioeconomic contexts. Furthermore, there is limited research on how supermarket access affects women's time allocation and broader household dietary outcomes.

For producers, supermarkets reorganize traditional agri-food value chains. In many developing countries, these chains are fragmented and characterized by low commercialization and the presence of many intermediaries including village brokers, processors, and wholesalers (Reardon et al., 2012). Supermarkets invest in establishing regional procurement networks and often bypass intermediaries to reduce transaction costs. As a result, modern value chains are geographically longer but vertically streamlined. These shifts can increase smallholder access to markets and raise farm incomes, as some studies have found (e.g., Nuthalapati et al., 2020; Ogutu et al., 2020).

However, there are also concerns that supermarkets may impose stringent quality standards, packaging requirements, and contractual obligations that are difficult for resource-poor farmers to meet without sufficient access to key inputs, technology, or credit (Andersson et al., 2015; Hernandez et al., 2007). Moreover, supermarket-driven consolidation may weaken smallholder bargaining power, raising concerns about equity in transactions (Hamilton et al., 2020; Sexton & Xia, 2018). Research in this field is insufficient. The existing literature mainly looks at horticultural farmers located near cities (e.g., Chang et al., 2015; Miyata et al., 2009; Ogutu et al., 2020), and little is known about the implications for remote farmers or those cultivating staple crops like grains.

Addressing these knowledge gaps is essential for inclusive retail modernization. Research that integrates nutrition, gender, and smallholder perspectives can guide supermarket expansion in line with multiple SDGs. In the context of China and other countries undergoing similar transitions, such evidence is critical to shaping agri-food policies that support nutrition, gender equality, and rural development.

1.3 The context of China

China has experienced one of the fastest supermarket expansions in the developing world over the past three decades. Like other countries, this expansion was initially driven by foreign direct investment (FDI) (Hu et al., 2004). After China joined the World Trade Organization (WTO) in 2001, multinational retailers such as Walmart and Carrefour began operating stores in large cities before gradually expanding also into smaller cities. Domestic supermarkets such as RT-Mart soon followed, entering smaller cities first to avoid direct competition with multinational supermarkets. Government initiatives, notably the "*Nonggaichao*" program that converts traditional free markets into supermarkets, further facilitated the spread of supermarkets into towns and rural areas (Reardon et al., 2012).

In recent years, supermarkets have expanded beyond processed foods into the retail of unprocessed or minimally processed products, including fresh vegetables, fruits, and meats (Maruyama et al., 2016). The pattern of one-stop shopping, which allows consumers to purchase both fresh and processed items under one roof, reduces time and transportation costs. This convenience has increasingly drawn consumers away from traditional wet markets. Furthermore, urbanization and income growth have shifted people's food preferences. The demand for more diverse, safer, better-packaged, and higher-quality foods, which are often more readily available in supermarkets, has grown rapidly. These structural changes have contributed to the growing dominance of supermarkets in China's food retail sector. Between 2000 and 2021, this sector has expanded rapidly, with sales increasing by more than 10% annually. By 2021, total food retail revenues reached 19.57 trillion Yuan (approximately 3.03 trillion USD), and supermarkets accounted for more than half of the market share (NBSC, 2022).

Child undernutrition in China has improved markedly. The child stunting rate declined from roughly 40% in 1995 to under 5% in 2017 (CNS, 2021).The child height gains across all age groups are also notable. On average, boys and girls grew approximately 3 cm per decade, indicating the improved long-term dietary quality. However, adolescent overweight and obesity rates had risen to about 19% by 2020, and this upward trend continues (NDCPA, 2021). In parallel, women's average daily time spent on food shopping and cooking decreased from about 130 minutes in 2008 to around 80 minutes in 2018 (NBSC, 2008, 2019).

These statistics imply a plausible relationship: supermarkets may contribute to reductions in child undernutrition and time burdens for women, but potentially at the cost of increased overnutrition risks including obesity due to greater consumption of processed foods. Yet, one should be cautious to interpret these trends as causal effects, because confounding factors are not accounted for. This dissertation disentangles the causal links between these factors in the subsequent chapters.

On the production side, rural households' nominal sales revenue from agricultural products nearly doubled between 2005 and 2015, rising from 7,730 Yuan to 15,761 Yuan per household (Ministry of Agriculture and Rural Affairs, 2010, 2017). Specifically, sales revenue from grains (e.g., rice, wheat, corn) increased by 172.8% (from 1,998 Yuan to 5,450 Yuan); horticultural products (i.e., vegetables and fruits) by 172.6% (from 1,304 Yuan to 3,555 Yuan); and livestock products(i.e., pork, beef, lamb, and poultry) by 28.2% (from 1,678 Yuan to 2,151 Yuan). Despite this growth, most transactions remained spot market-based, with fewer than 10% occurring through advance contracts.

However, the low prevalence of contract farming does not imply that supermarkets are uninvolved in transactions. In fact, as supermarkets increasingly coordinate with processors and wholesalers to dictate product selection, quality standards, volumes, and pricing, these shifts inevitably influence farmgate incomes and farmers' production decisions (Hamilton et al., 2020; Sexton & Xia, 2018). This dissertation is particularly interested in the impact of supermarkets on grain farmers in China, both because grain sales constitute the largest farm income source for many rural households and because of the high prevalence of grain farming in China's agricultural landscape.

1.4 Research objectives and outline

The previous sections have described the nutritional, time-use, and income-related challenges faced by children, women, and smallholder farmers, and highlighted the potential role of supermarkets in addressing these issues. The previous sections have also identified the key knowledge gaps in the existing literature. This dissertation pursues three central research objectives:

- **Objective 1:** To estimate the impact of supermarket access on children's nutrition, using both dietary intake and anthropometric indicators.
- **Objective 2:** To identify the causal relationship between supermarket expansion and changes in women's food shopping and cooking time, and to examine the potential trade-off between reduced time and dietary quality.
- **Objective 3:** To evaluate how supermarket expansion affects the incomes of smallholder grain farmers and their allocation of productive resources.

These objectives are addressed in the three empirical chapters of the dissertation. Chapter 2 addresses the first objective by presenting the first empirical study of supermarket effects on child nutrition in China, and, to our knowledge, the first in any country to use panel data with individual-level dietary indicators. It measures child nutrition using both short-term and long-term indicators. Short-term indicators include dietary diversity scores and intakes of macro- and micronutrients, while long-term indicators include anthropometric outcomes such as body weight and height. The analysis also explores heterogeneous effects across subgroups: rural versus urban children, boys versus girls, and children from low-income versus high-income households.

Chapter 3 focuses on the second objective. It establishes a causal link between the expansion of supermarkets and reductions in women's time spent on food shopping and cooking. While this relationship has been hypothesized in prior studies, it has not been empirically tested using quantitative data. Beyond identifying this causal relationship, this chapter also investigates potential trade-offs between time savings and dietary quality. Specifically, this study examines the supermarket impact on adult diets. Dietary outcomes are assessed using both conventional indicators, such as dietary diversity, nutrient intake, and anthropometrics, and a food processing-based classification that distinguishes dietary intake from unprocessed, moderately processed, and highly processed foods. By doing so, this chapter answers whether and to what extent the time savings facilitated by supermarkets may lead to declines in dietary quality, and whether such declines could signal longer-term risks associated with increased consumption of processed foods.

Chapter 4 addresses the third objective. It involves the effects of supermarket on the welfare of smallholder farmers. Different from most existing studies focusing on horticultural farmers located in sub-city areas, this study investigates the effects of supermarket expansion on the income of grain farmers across diverse rural contexts in China. We propose a location-based framework to discuss the potential heterogenous effects on peri-urban and remote farmers and provide empirical evidence using nationwide household panel data and unique geospatial supermarket data. This study also examines both direct mechanisms, including farm-gate price and commercialization rate, and indirect mechanisms, including the allocation of household productive resources (i.e., land, labor, and purchased inputs). This chapter highlights a potential spontaneous transformation among farmers driven by adaptive diversification strategies in response to supermarket expansion.

Chapter 5 concludes the dissertation by synthesizing the findings and drawing policy implications that support inclusive and sustainable retail modernization.

CHAPTER 2

Impacts of Supermarkets on Child Nutrition in China

Abstract

In many emerging countries, agri-food value chains are transforming rapidly. One emblematic trend is the proliferation of supermarkets and other modern retailers. Supermarkets affect the way supply chains are organized and may also influence the types of foods purchased and eaten by consumers. Research on what this means for people's diets and nutrition is still relatively scant. Here, we analyze the effects of supermarkets on child diets and nutrition in China, using nationally representative panel data with information on households' access to supermarkets and individual-level dietary and anthropometric indicators. Employing a variety of difference-in-difference approaches, we find that improved access to supermarkets leads to higher child dietary diversity and nutrient intakes, especially among children in rural areas and from low-income households. Supermarkets are also found to increase child height, but not weight. The positive nutritional effects are mediated through supermarkets contributing to more variety in local food supplies and lower average food prices. Our findings suggest that the spread of supermarkets has improved child dietary quality and nutrition in China.

Keywords: food environments, supermarkets, child malnutrition, dietary quality, panel data

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2.1 Introduction

Agri-food value chains in emerging countries have been transforming rapidly during the past two decades, considerably reshaping the patterns of food production and consumption (Barrett et al., 2022; Bellemare et al., 2022). Food environments – defined as the places where people interact with the food system to acquire and consume food – are the critical channel through which agri-food value chains influence dietary choices and nutrition (FAO, 2016). Often as an integral part, or even a trigger, of value chain transformation, food environments are also changing rapidly. One notable trend is the proliferation of supermarkets and other modern retailers, especially in urban areas but increasingly also in rural areas (Barrett et al., 2022). In many parts of Latin America and Asia, and in some parts of Africa, supermarkets have already gained sizeable market shares in food retailing (Gorton et al., 2011; Khonje et al., 2020; Reardon et al., 2003). Supermarkets do not only affect the place of purchase, but often also the types of foods supplied as well as food accessibility and prices (Qaim, 2017; Wanyama et al., 2019).

In comparison to traditional wet markets and street vendors, supermarkets often provide a wider variety of processed and unprocessed foods with more standardized quality and safety, which may be associated with nutritional improvements. However, there are also claims that supermarkets in many places have a strong focus on selling ultra-processed foods and convenience products, which could contribute to unhealthy diets and negative nutritional outcomes. Better understanding the effects of supermarkets on people's diets and nutrition in different contexts is useful for developing policies that can promote fair and healthy food environments. Here, we analyze the effects of supermarkets on diets and nutrition among children in China with nationally representative panel data. Healthy nutrition during childhood is pivotal for physical growth, cognitive development, and human capital accumulation during the life course. Unfortunately, many children in emerging countries, including China, suffer from poor diets and nutritional deficiencies with long-term negative effects for human and economic development (Alderman & Fernald, 2017; UN, 2022). Improving child diets and nutrition is therefore an important development priority.

Several studies analyze nutritional effects of supermarkets in different countries, but most of this existing work focuses on nutritional outcomes in adults. A common finding is that the spread of supermarkets is associated with a higher body mass index (BMI) and a higher likelihood of overweight and obesity among adults (Demmler et al., 2018; Demmler et al., 2017;

Otterbach et al., 2021; Rummo et al., 2017). Much less is known about the effects on child nutrition. A few studies look at children and find no significant association between supermarkets and child overweight and obesity (Debela et al., 2020; Kimenju & Qaim, 2016; Zhou et al., 2021), while one study reports a positive association for children from high-income households in Indonesia (Umberger et al., 2015). Important to stress is that data on overweight and obesity alone can only provide a partial picture of nutrition, as nutritional quality is not only a function of food energy but also of dietary diversity and micronutrient intakes. In fact, micronutrient deficiencies are widespread, including in countries with rapidly rising rates of overweight and obesity (UNICEF et al., 2021).

A few studies examine effects of supermarkets on dietary choices, mostly using household-level food consumption data. Better access to supermarkets is often associated with higher consumption of processed and lower consumption of unprocessed foods (Asfaw, 2008; Demmler et al., 2018; Rischke et al., 2015). In some situations, supermarkets also seem to be associated with higher consumption of animal-sourced foods such as meat and dairy (Debela et al., 2020; Seto & Ramankutty, 2016). A handful of studies also show positive associations between supermarket use and dietary quality indicators, such as dietary diversity scores or the healthy eating index (Nandi et al., 2021; Ren et al., 2022).

We are aware of only one study that uses individual-level dietary intake data from children to analyze supermarket effects, namely Khonje et al. (2020) with a sample from Lusaka, the Capital City of Zambia. Khonje et al. (2020) show that children living in households that use supermarkets regularly have higher protein and micronutrient intakes, higher child height-for-age Z-scores, and lower rates of stunting. But this study in Zambia only looks at one large city, so the external validity is limited. Moreover, it uses cross-sectional data, which has drawbacks in terms of addressing possible endogeneity issues.

We contribute to the literature in four ways. First, we use nationally representative panel data and employ various difference-in-difference (DID) methods to evaluate the effects of supermarkets on child diets and nutrition in China, which has not been done before. Second, we construct different dietary quality and nutrition indicators, including child dietary diversity scores and intakes of food energy, protein, and various micronutrients. We also use child anthropometric measures, including height-for age and BMI-for-age Z-scores. Third, we compare effects across sociodemographic and geographical contexts, considering differences between age, gender, and income groups, as well as between rural and urban areas. Fourth, we analyze possible impact pathways looking at the role of supermarkets for food variety and local food prices.

The remainder of this article is structured as follows. Section 2 provides some background on changing agri-food value chains, in addition to describing the spread of supermarkets in China and likely implications for dietary choices and nutrition. Section 3 discusses the data, the key variables, and the econometric approaches used. Section 4 presents and discusses the results with different model specifications, while section 5 concludes.

2.2 Background and conceptual framework

2.2.1 Transformation of agri-food value chains

Over the last few decades, agri-food value chains have been undergoing a rapid transformation, with far-reaching implications for farmers, workers, traders, consumers, and other stakeholders involved (Antràs, 2020; Barrett et al., 2022; Bellemare & Lim, 2018; Lim, 2021; Lim & Kim, 2022; Qaim, 2017; Reardon et al., 2012). Elements of this transformation include shifts towards higher-value products, stricter quality, safety, and sustainability standards, and higher degrees of international and vertical integration, just to name a few. These developments are driven by multiple supply- and demand-side-related factors, such as new technologies, market-oriented reforms, new trade and investment opportunities, urbanization trends, rising incomes, and evolving lifestyles.

One important characteristic of the agri-food value chain transformation, especially in the context of emerging countries, is the growth of supermarkets and other modern retailers. While in most high-income countries, supermarkets were established and gained significant market shares already in the 1960s, in low- and middle-income countries these developments only started in the 1990s, first in Latin America and parts of Asia, and later also in Africa (Reardon et al., 2003). Supermarkets change the way food is procured from farmers and traded. In many emerging countries, supermarkets and/or processing companies have marketing contracts with farmers in order to ensure consistent supply of high-quality produce (Bellemare et al., 2022; Qaim, 2017). Contracting may change farming structures and may also influence traditional food traders and markets (Nuthalapati et al., 2020). For consumers, the growth of supermarkets, at the expense of more traditional food retailers, is associated not only with changes in terms of the place of purchase, but possibly also in term of the types of foods offered, food prices, and shopping atmosphere (Demmler et al., 2018; FAO et al., 2023; Hawkes, 2008; Kimenju et al., 2015).

In some Asian countries, government investment and incentive policies have been established to specifically support the expansion of supermarkets in order to improve food availability for urban and rural consumers (Reardon et al., 2012). In China, the government views supermarkets as a tool for stabilizing agricultural supply chains and modernizing food retailing.[1] Over the last two decades, a series of policies, such as the "*Nonggaichao*" program (converting traditional wet markets into supermarkets) induced in 2003, have been implemented in China to encourage supermarket development (Hu et al., 2004). Consequently, the number of supermarkets in the country more than tripled between 2002 and 2010, and has stayed at a high level since then (Fig. A1 in the Appendix).

2.2.2 Supermarket expansion and child nutrition in China

Fig. 2.1 shows that – in parallel to the expansion of supermarkets – China was successful in reducing rates of child stunting considerably. The two trends are not necessarily causally related, even though supermarkets could – in principle – improve diets and nutrition in several ways. First, supermarkets often offer a larger variety of foods than traditional food stores (Reardon et al., 2003; Qaim, 2017). While many of the foods offered in supermarkets are processed, larger food variety can still contribute to higher dietary diversity. Processed foods with longer shelf-lives can also stabilize food supply and reduce seasonal fluctuations. Important to note is that supermarkets try to adjust to local dietary cultures. In China, fresh foods are popular and many consumers are used to shop frequently rather than storing processed foods for a longer period of time (Maruyama et al., 2016). Hence, many supermarkets in China offer an increasing variety of fresh foods; some also mimic modern versions of wet markets within their stores, so that consumers can satisfy all their shopping preferences under one roof.

Beyond food variety, positive nutritional effects can also be mediated through lower food prices. A conventional view is that supermarkets offer foods at higher prices than traditional markets because of higher costs associated with physical assets (e.g., buildings and equipment) and services (e.g., sorting, packing, and refrigerating) (Goldman et al., 2009). However, evidence from various emerging countries shows that supermarkets tend to be more expensive than traditional markets in the beginning, but then become more price-competitive over time,

[1] As mentioned in Chinese government documents (http://www.gov.cn/test/2006-02/22/content_207415.htm).

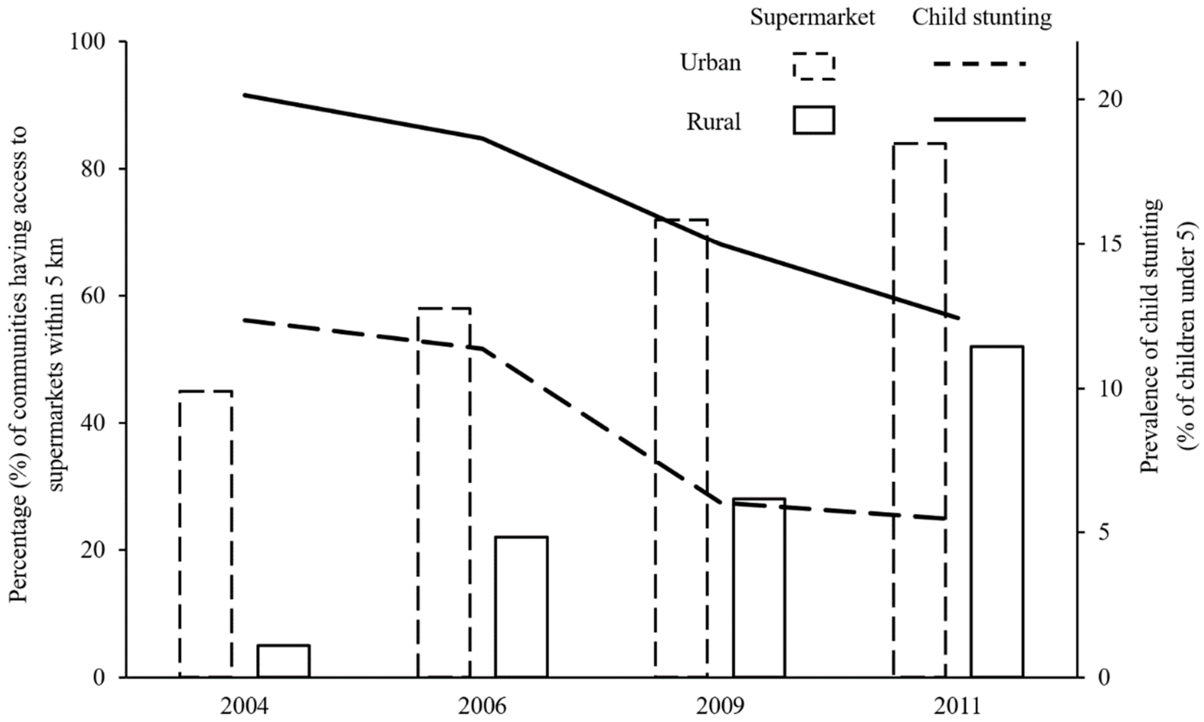

Fig. 2.1 Supermarket expansion and child stunting in China (2004-2011)
Source: Based on data from the China Health and Nutrition Survey.

especially for processed foods, due to economies of scale (Hawkes, 2008; Rischke et al., 2015). Recent studies also suggest that supermarkets may contribute to lowering the prices of certain fresh foods at local and regional levels by increasing market efficiency (Atkin et al., 2018; Bergquist & Dinerstein, 2020; Minten et al., 2010; Yuan et al., 2021). The entry of supermarkets adds to market competition. Moreover, supermarkets often foster vertical integration of food supply chains, leading to fewer intermediaries and reduced transaction costs (Gale & Hu, 2012; Nuthalapati et al., 2020).

On the other hand, supermarkets can also contribute to negative nutritional outcomes. While supermarkets sell all types of foods, healthy and unhealthy ones, advertisement and promotional activities may lure consumers to choose more ultra-processed foods that are often rich in terms of energy and salt but poor in terms of protein and micronutrients. Overconsumption of ultra-processed foods contributes to overweight and obesity. Moreover, especially in children, high consumption of energy-dense processed foods may lead to a crowding out of more nutrient-dense foods, thus potentially resulting in lower-quality diets. Childhood obesity is rising in middle-income countries including China (UN, 2022), and so far, it is not clear whether the spread of supermarkets is contributing to this trend.

2.3 Materials and methods

2.3.1 Survey data

The data used here come from the China Health and Nutrition Survey (CHNS), which is nationally representative. CHNS is a collaborative project by the Chinese Center for Disease Control and Prevention and the University of North Carolina in the USA and is still ongoing. This longitudinal survey has been conducted in twelve provinces and three municipalities in China since 1989, including well-developed and less-developed regions. In each province, two prefecture-level cities and four counties were randomly selected. Then, communities, households, and individuals were randomly selected in these cities and counties. The total sample includes over 4,000 households and 11,000 individuals.

We use variables from three CHNS datasets. First, the individual dataset contains detailed dietary intakes for three consecutive days, as well as anthropometric data, including body weight and height measurements. Dietary intake is collected by asking individuals or their caregivers to report all foods consumed at home and away from home during the last 24 hours. Second, the household dataset includes household food consumption for the same three days and a large set of socioeconomic characteristics. Household food consumption is obtained by computing inventory changes from the beginning to the end of each day, combining weighing all purchased and home-prepared foods. In our analysis, we rely on the individual intake data for children but supplement these data with the consumption of spices, condiments, and edible oils from the household dataset. We also use the household consumption data to check for and resolve possible severe discrepancies. Third, the community dataset contains information on the availability of local services, including supermarkets.

An advantageous feature of the CHNS is that the dietary data are collected under the supervision of nutritionists and the anthropometric data are measured by medical staff. This helps reduce measurement error. We use data from four survey waves (2004, 2006, 2009, and 2011). Waves before 2004 cannot be used because data on supermarket access were not collected. Waves after 2011 cannot be used because individual-level dietary data have not been released. However, as much of the supermarket growth in China occurred during the 2000s (Fig. A1), the time period from 2004 to 2011 perfectly captures the variation of interest in this study.

The children included in our sample are aged 2 to 17.9 years with diverse socioeconomic backgrounds from urban and rural households. While in the nutrition literature the focus is often primarily on young children, dietary quality is known to also affect body development in older children and adolescents (Rogol et al., 2000). This is why we consider children up to the age of 17.9 years. Another advantage of using this broad age range is that more individuals in our panel remain in the sample over several survey waves, thus increasing the estimation efficiency. Yet, in addition to looking at the whole sample we also differentiate between younger and older children, looking at those below and above 6 years of age, respectively.

After excluding observations with missing values for some of the variables and extreme outliers (unreasonable calorie and nutrient intakes), our full sample is an unbalanced panel with 6,316 child observations. Specifically, we use 1,771; 1,517; 1,379; and 1,649 observations from 211; 211; 193; and 253 communities in 2004; 2006; 2009; and 2011, respectively. In a robustness check, we also analyze effects with a balanced panel, only using data from children included in all four survey waves. In addition, we test for possible attrition bias and find that attrition is not correlated with any of the main variables of interest (Table A19 in the Appendix).

Our main objective is to estimate the effects of supermarket access on child diets and nutrition. In the following we first explain how we measure the key variables before describing the econometric approaches in more detail.

2.3.2 Measuring supermarket access

Supermarket access is the key explanatory variable in this study. It can be measured in different ways. One approach is to evaluate the actual use of supermarkets by households or individuals. For instance, several studies use a dummy variable that takes a value of one if a household used a supermarket for any of its food purchases (Demmler et al., 2018; Debela et al. 2020). Other studies look at the amount or the share of money spent on supermarket food purchases (Asfaw, 2008; Kimenju et al., 2015; Umberger et al., 2015). Another approach is to evaluate the availability of supermarkets in a certain setting. For instance, several studies use a dummy based on the presence of a supermarket within a certain radius around the household (Allcott et al., 2019; Zeng et al., 2019), or look at the distance between the household and the closest supermarket (Drewnowski et al., 2012; Otterbach et al., 2021; Ren et al., 2022). Here, we use the second approach and focus on the local availability of supermarkets, as this is the type of information included in CHNS.

CHNS defines supermarkets as larger-sized self-service stores that sell a bigger variety of foods and non-food products than traditional grocery stores. The community survey includes data on the number of supermarkets within a 5 km radius of each community. In our study, we measure supermarket access through a dummy variable that takes a value of one if at least one supermarket exists within 5 km of a child's residence community, which means that a supermarket is located either within the community or relatively nearby. Communities in China are generally compact (Xi et al., 2011), so the community represents the household locations sufficiently well. Using this dummy variable, the diffusion of supermarkets in China is visualized in Fig. A2 in the Appendix. By 2011, around 65% of the surveyed communities had access to a supermarket within 5 km.

As an alternative variable, we use proximity to a supermarket based on the distance between a community and the closest supermarket.[2] However, we only use this alternative for robustness checks, not as our main supermarket variable, because proximity in our context has two potential drawbacks. First, CHNS does not set a threshold for collecting the distance, therefore some communities have a distance measure also when the closest supermarket is more than 5 km away, while others do not. Hence, measurement error may be an issue. Second, proximity based on distance at a small local scale may possibly be associated with selection bias, as households may choose their place of residence based on unobserved preferences. Supermarkets are often located near busy streets with excessive noise and air pollution, so that households that can afford may deliberately keep some distance from these places (Peris & Fenech, 2020).

2.3.3 Measuring diet and nutrition outcomes

Dietary diversity scores. The child dietary diversity score (CDDS) is considered a good and easy-to-measure proxy of child dietary quality (Fongar et al., 2019). CDDS is calculated as the number of food groups consumed by the child during the last 24 hours. In our case, we calculate the average number of food groups consumed by each child during the three survey days.

We use two versions of CDDS with different food group classifications (Table 2.1). The first version is the Chinese CDDS with a total of nine food groups, building on the guidelines of the Chinese Children's Food Guide Pagoda (CCFGP) 2022. CCFGP 2022 was created by the Chinese Nutrition Society, aiming to recommend daily food consumption quantities that satisfy the requirements of children's healthy growth. The second version is the WHO CDDS based on

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[2] The continuous proximity variable is generated as:

$$Proximity = \ln\left(\frac{1}{distance\ to\ the\ nearest\ supermarket} + 1\right)$$

where proximity=0 if the community has no access to a supermarket or no distance was recorded, suggesting the distance approaches infinity.

seven food groups (WHO, 2008).[3] While both versions aim to proxy child dietary quality, the focus is slightly different. The Chinese CDDS emphasizes the variety of foods consumed, the WHO CDDS cares more about the minimum dietary quality.

Table 2.1 Two versions of child dietary diversity scores (CDDS)

Number	Chinese CDDS	WHO CDDS
1	Staples (grains and potatoes)	Grains, roots, and tubers
2	Vegetables	Flesh foods (meat, fish, poultry, and liver/organ meats)
3	Fruits	Eggs
4	Meat and poultry	Dairy products (milk, yoghurt, and cheese)
5	Eggs	Legumes and nuts
6	Aquatic products (fish and shrimp)	Vitamin A rich fruits and vegetables
7	Milk and its products	Other fruits and vegetables
8	Legumes and nuts	
9	Edible oil	

Nutrition index. A healthy diet must satisfy children's needs for energy and all essential nutrients. Drawing on Busgang et al. (2022), we construct a nutrition index (NI) considering the intakes of calories, protein, and various micronutrients, namely vitamins A, C, and E, calcium, iron, and zinc.[4] At first, we calculate the three-day average intakes of these nutrients by matching individual consumption quantities of all food items with the China Food Composition Tables. Then, we compare the real intake with the recommended intake to assess the sufficiency level for each nutrient j:

$$Sufficiency\ level_j = \begin{cases} \dfrac{real\ intake_j}{recommended\ intake_j} & if \quad real\ intake_j < recommended\ intake_j \\ 1 & if \quad real\ intake_j \geq recommended\ intake_j \end{cases}, j = 1, 2 \cdots, 8 \quad (1)$$

[3] The WHO CDDS was originally developed to evaluate the minimum dietary diversity of children under 23 months, but recent studies suggest that it can also be a useful indicator for older children (Fongar et al., 2019).

[4] While the body needs more nutrients, this set of macro- and micronutrients provides a comprehensive picture of a child's dietary and nutrition situation.

Finally, the NI is calculated as the sum of the eight sufficiency levels:

$$Nutrition\ index\ (NI) = \sum_{j=1}^{8} Sufficiency\ level_j \qquad (2)$$

Thus, the NI can take any value between 0 and 8. In separate versions of the NI, we use two different child age- and sex-based recommended intake levels, namely those from the Chinese Nutrition Society (CNS, 2000) and from the joint FAO/WHO expert consultation (FAO & WHO, 2004). The CNS-recommended levels refer to the intake level of nutrients that can meet the requirements of the vast majority (nearly 98%) of individuals in the specific age and sex groups. The FAO/WHO-recommended levels are lower, as they refer to the mean nutrient requirements of healthy and well-nourished individuals in the specific age and sex groups.

Nutritional status. Nutritional status is commonly evaluated with anthropometric indicators, such as body height, weight, or BMI. For children, age also needs to be considered. We use the height-for-age Z-score (HAZ), which is the most comprehensive indicator of longer-term healthy nutrition, as it reflects the body's biological response to continued nutrient intake. Furthermore, we calculate BMI-for-age Z-scores (BAZ). In these calculations, we use the WHO Child Growth Standards (WHO, 2006). The Z-score indicates the number of standard deviations (SD) that the individual child is above or below the median of the same-age reference population. Originally developed to assess the nutritional status of children under five, the validity of HAZ and BAZ and the newer WHO Growth Standards have been extended to older children aged 5-19 (de Onis et al., 2007). In addition to these continuous Z-scores, we generate three dummy variables: (a) underweight, defined as a weight-for-age Z-score (WAZ) below -2 SD; (b) overweight, defined as BAZ > +1 SD; and (c) obesity, defined as BAZ > +2 SD.

2.3.4 Control variables

Child diet and nutrition outcomes may be influenced by supermarket access, but also by various other socioeconomic variables, which we need to control for in the analysis. Individual-level controls that we use include child age, sex, education, and physical activity. In terms of household-level variables, we control for per capita income, parental education, dietary knowledge, household size, ownership of a refrigerator, car, or motorcycle, and diversity of household agricultural production. Dietary knowledge is measured as a score, using answers of the child's mother to ten nutrition-related questions (Table A1 in the Appendix). Agricultural production diversity, which can affect the diets of rural households in particular, is measured by counting the number of household cropping, livestock, fishing, and home gardening activities.

At the community level, we control for the availability of traditional wet markets, which are still important sources of food purchases for many households. In addition, we control for the availability of restaurants, including traditional ones and fast-food restaurants. Finally, we use a dummy variable indicating whether a bus stop is available in the community because residents may rely on public transport to reach supermarkets and other shops located outside of the community. Table A2 in the Appendix lists all explanatory variables used in the econometric models with descriptive statistics.

2.3.5 Econometric approach

We evaluate the effects of supermarkets on child diets and nutrition with panel data econometric models of the following type:

$$Y_{it} = \alpha + \beta SM_{it} + \gamma X_{it} + u_{it} \quad (3)$$

where Y_{it} refers to the diet and nutrition indicators of individual child i in year t, SM_{it} is supermarket access, X_{it} represents the vector of control variables, and u_{it} is a random error term. We are particularly interested in the coefficient β.

As a starting point, we use the standard two-way fixed effects (TWFE) approach to estimate equation (3), including individual fixed effects to control for observed and unobserved time-invariant characteristics as well as time (year) fixed effects. We also use year-by-region fixed effects to control for unobserved time-variant heterogeneity at region level, and year-by-month fixed effects to control for seasonal differences.

However, in our study where the entry of supermarkets occurs at different points in time across communities (staggered design), the standard TWFE estimates may be contaminated by a "negative weighting" problem resulting from "bad" treatment combinations, as pointed out in recent work (Borusyak et al., 2024; Callaway & Sant Anna, 2021; de Chaisemartin & D Haultfœuille, 2023a; Sun & Abraham, 2021). We address this concern by using the alternative estimator proposed by de Chaisemartin and D'Haultfoeuille (2023) (hereafter, the CDH method, or also CDH DID) as a second approach. The CDH estimator is robust to treatment timing and effect heterogeneity (de Chaisemartin & D'Haultfœuille, 2024). We mainly rely on the CDH results, unless otherwise noted.

As a third method, we use a matched-sample DID strategy (matched DID). For this, we generate a two-period panel data set with two separate groups: (a) individuals without supermarket access in both periods, and (b) individuals without supermarket access in the first period, but with supermarket access in the second period (see Table A3 in the Appendix for details of this approach). Then, we apply propensity score matching to match samples based on individual, household, and regional variables in the first period to ensure that the two groups have similar characteristics except for supermarket access. Finally, the supermarket effects are estimated using the classical DID method. Compared to the standard TWFE method, the matched DID using two-period data can avoid the "negative weighting" problem, but – given that it only compares two artificially created periods—it ignores the dynamic effects of supermarkets. Therefore, the matched DID is not our preferred method but is used as an additional robustness check.

Food preferences and dietary patterns may be more similar within communities than across communities (Cooke & Wardle, 2005). Moreover, there may be systematic differences between boys and girls. Hence, we cluster standard errors at the community-sex level to resolve potential correlation in the error term u_{it} in all regressions. Alternative clustering methods are also used to check the robustness.

In addition to the average effects of supermarket access on child diets and nutrition, we are also interested in heterogeneous effects for different subsamples. The wide age range of children and adolescents in the sample allows for the assessment of heterogeneous outcomes across different age groups. Differences between male and female individuals are also of interest. Additionally, previous studies show that food insecurity and nutrient deficiencies are particularly severe among rural populations and low-income households (Gao et al., 2022). Accordingly, we estimate heterogeneous effects for younger versus older children, for boys versus girls, for children from low- versus higher-income households, and in rural versus urban areas.

2.3.6 Parallel trends and placebo tests

In spite of using three different panel data estimators to address endogeneity issues, one may still worry about bias due to (a) different dietary trends across communities, even before the entry of supermarkets and (b) possible reverse causality. We address these concerns in three ways. First, our data with more than two waves allow us to check for trends in the sample also before the entrance of supermarkets. We examine the parallel trends assumption by estimating a dynamic version of the CDH model. Second, we regress the presence of supermarkets in period t on dietary outcome and control variables in period $t-1$, as follows:

$$SM_{it} = \rho + \lambda Y_{it-1} + \pi X_{it-1} + \vartheta_i + \delta Z_{t-1} + \varepsilon_{it-1} \quad (4)$$

where ϑ_i represents individual or household fixed effects, and Z_{t-1} is time fixed effects. The other controls are the same as those in equation (3). A significant coefficient λ would be an indication that there is either a different trend between observations with and without supermarket access, even before a supermarket was established, or reverse causality, meaning that supermarkets are more likely to be established in locations with certain dietary patterns. However, an insignificant λ would be reassuring for the exogeneity of supermarket entry and a causally identified β in equation (3).

Third, in a placebo test we separately analyze effects of supermarkets on energy and nutrient intakes at home and away from home.[5] This test assumes that supermarkets influence child diets primarily through foods eaten at home. In contrast, if the supermarket effects were spurious and only due to correlation with unobserved time-variant factors in the supermarket locations, we would expect to see significant effects on both intakes at home and away from home. In other words, if in this placebo test supermarkets were significantly associated with intakes away from home, equation (3) would fail to rule out unobserved time-variant factors, and the estimated effects of supermarkets would likely be biased.

2.4 Results

2.4.1 Descriptive results

Table A4 in the Appendix shows mean child dietary outcomes by survey wave. Dietary diversity increased constantly between 2004 and 2011, as indicated by both the Chinese CDDS and the WHO CDDS. However, the nutrition index remains low with values significantly smaller than 8, suggesting that nutrient deficiencies are still a widespread problem among Chinese children. Table A4 also shows calorie and nutrient intakes. Vitamin A and calcium intakes increased significantly between 2004 and 2011, whereas calorie intakes dropped. This may be due to dietary shifts over time with carbohydrates losing in relative importance (Table A5 in the

[5] The CHNS collects the places of all food items consumed, including at home, at nursery school, school, or work, at restaurants or food stands, in the house of relatives or friends, at festival/celebrations, and others. We calculate the intake away from home as everything not eaten at home.

Appendix). Intakes of other nutrients remained constant or even declined slightly in some cases. However, Table A4 also shows that the mean age of children in the sample decreased between 2004 and 2011, so that a slight decline in nutrient intakes cannot necessarily be interpreted as a nutritional deterioration. We control for child age in the econometric analysis.

The lower part of Table A4 indicates a continuous increase in child HAZ and a reduction in child underweight. On the other hand, we also observe an increase in BAZ, overweight, and obesity. By 2011, about 23% of the children were overweight and 10% were obese. To what extent these changes may be related to supermarkets is analyzed more formally below.

Table 2.2 shows mean DDS and NI for children in communities with and without supermarket access. In all survey waves, children in communities with supermarket access have higher dietary diversity and higher levels of nutrient adequacy than children in communities without supermarket access.

Table 2.2 DDS and NI of children with and without supermarkets access

	2004			2011		
	Supermarkets within 5 km			Supermarkets within 5 km		
	Access	No access	Diff.	Access	No access	Diff.
Chinese DDS	6.14	5.21	0.93***	6.57	5.74	0.83***
	(1.18)	(1.00)		(1.23)	(1.10)	
WHO DDS	4.30	3.54	0.76***	4.67	3.95	0.71***
	(0.96)	(0.89)		(1.00)	(0.92)	
Chinese NI	4.92	4.51	0.42***	4.68	4.12	0.56***
	(1.25)	(1.23)		(1.32)	(1.27)	
FAO/WHO NI	6.11	5.79	0.32***	6.01	5.58	0.43***
	(0.96)	(0.95)		(1.10)	(1.08)	
N		1,771			1,649	

Notes: Mean values are shown with standard deviations in parentheses. Differences between the two groups in 2006 and 2009 (not shown) are similar as in 2004 and 2011. *** indicates significance at the 1% level.

Table A6 in the Appendix compares CDDS and NI by region, child sex, income, and age groups. Urban children and children from high-income households show better dietary outcomes than rural children and children from low-income households. Girls have a somewhat lower NI than boys, and younger children tend to have healthier diets than older children, pointing at certain dietary inequalities. Whether supermarkets have different effects on these subsamples will be analyzed below.

2.4.2 Mean effects of supermarkets on child diets

Table 2.3 reports the effects on dietary diversity, using the panel data models explained in equation (3) above. We use the Chinese CDDS and the WHO CDDS as dependent variables, respectively. Models (1)-(3) and (6)-(8) present results obtained with the standard TWFE

Table 2.3 Mean effects of supermarkets on child dietary diversity scores (CDDS)

	Dependent variable: Chinese CDDS				
	TWFE			CDH DID	Matched DID
	(1)	(2)	(3)	(4)	(5)
Supermarket	0.304***	0.187**	0.287***	0.175***	0.179**
	(0.076)	(0.077)	(0.075)	(0.072)	(0.091)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	Yes
Year-by-region FE	No	Yes	No	No	No
Year-by-month FE	No	No	Yes	No	No
N	6,316	6,316	6,316	6,316	2,422
	Dependent variable: WHO CDDS				
	TWFE			CDH DID	Matched DID
	(6)	(7)	(8)	(9)	(10)
Supermarket	0.304***	0.231***	0.280***	0.205***	0.215***
	(0.066)	(0.069)	(0.064)	(0.069)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	Yes
Year-by-region FE	No	Yes	No	No	No
Year-by-month FE	No	No	Yes	No	No
N	6,316	6,316	6,316	6,316	2,422

Notes: ** and *** indicate significance at the 5% and 1% level, respectively. Standard errors clustered at the community-sex level are shown in parentheses. Full TWFE results with all covariates included are shown in Table A7 in the Appendix.

estimator. Models (4) and (9) present effects after one period of supermarket access obtained with the CDH DID estimator. Models (5) and (10) are estimates obtained with the matched DID approach. In all models, we use individual fixed effects, but the models differ in terms of the inclusion of year fixed effects, year-by-region fixed effects, and year-by-month fixed effects, as indicated in Table 2.3. As can be seen, supermarket access increases the Chinese CDDS by 0.18-0.30 food groups and the WHO CDDS by 0.21-0.30 food groups. This is equivalent to about 25-35% of the observed rise in child dietary diversity between 2004 to 2011, clearly suggesting that supermarkets contributed to child dietary improvements in China.

Table 2.4 presents the effects on nutrition index. We use the Chinese NI and FAO/WHO NI as dependent variables, again using the three different estimators. Supermarket access increases the Chinese NI by 0.24-0.38 and the FAO/WHO NI by 0.18-0.28. Given that the mean values of both types of NI barely changed between 2004 and 2011, these nutritional improvements through supermarket access are considerable. All results are quite consistent across the different model specifications.[6]

In a robustness check, we use the proximity to supermarkets instead of the supermarket access dummy as explanatory variable in the regression models. Results are shown in Table A10 in the Appendix. They confirm the significantly positive effects of supermarkets on CDDS and NI. In a different robustness check, we use an alternative clustering approach for the standard errors. In the main models in Tables 2.3 and 2.4, we cluster standard errors at the community-sex level. In the alternative specification in Table A11 in the Online Appendix, we cluster standard errors at the community level. The estimates and significance levels remain almost unchanged. We also find positive and significant effects of supermarkets on child diets with a balanced panel, only using observations from children included in all four survey waves (Fig. A3 in the Appendix).

To supplement and further reinforce the validity of our findings, we also evaluate the effects of supermarkets on the intake of each nutrient separately (Table A12 in the Appendix).

[6] In principle, the results may indicate positive dietary effects through supermarket entry or also negative effects through supermarket closure. Very few communities (only 10 in our sample) experienced supermarket closure (Fig. A2), hence the effects in Tables 2.3 and 2.4 primarily represent dietary improvements through supermarket entry. In a separate analysis, we estimated the effects of supermarket closure with the relevant subsample (Table A9 in the Appendix). Indeed, even though the number of observations is small, the estimates suggest a worsening of child dietary quality through supermarket closure.

Supermarket access increases the child intake of calories, protein, and almost all micronutrients.

Table 2.4 Mean effects of supermarkets on child nutrition index (NI)

	Dependent variable: Chinese NI				
	TWFE			CDH DID	Matched DID
	(1)	(2)	(3)	(4)	(5)
Supermarket	0.376***	0.349***	0.381***	0.258***	0.243**
	(0.101)	(0.100)	(0.097)	(0.095)	(0.123)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	Yes
Year-by-region FE	No	Yes	No	No	No
Year-by-month FE	No	No	Yes	No	No
N	6,316	6,316	6,316	6,316	2,422
	Dependent variable: FAO/WHO NI				
	TWFE			CDH DID	Matched DID
	(6)	(7)	(8)	(9)	(10)
Supermarket	0.279***	0.244***	0.278***	0.184***	0.186**
	(0.082)	(0.082)	(0.079)	(0.072)	(0.093)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	Yes
Year-by-region FE	No	Yes	No	No	No
Year-by-month FE	No	No	Yes	No	No
N	6,316	6,316	6,316	6,316	2,422

Notes: ** and *** indicate significance at the 5% and 1% level, respectively. Standard errors clustered at the community-sex level are shown in parentheses. Full TWFE results with all covariates included are shown in Table A8 in the Appendix.

We then perform the parallel trends test and the placebo test. Fig. 2.2 displays the parallel trends test results, using the CDH estimator. The coefficients in the survey wave prior to the entry of supermarkets are statistically insignificant (all close to zero). There are no discernible pre-trends. Fig. 2.2 also reveals increasing treatment effects of supermarkets over time in the post-treatment periods. This increase may be due to gradual shifts in dietary choices. Moreover, supermarkets are likely to start with a smaller food product portfolio when opening a new outlet and then increase food variety and adjust prices over time. These mechanisms are discussed in more detail below.

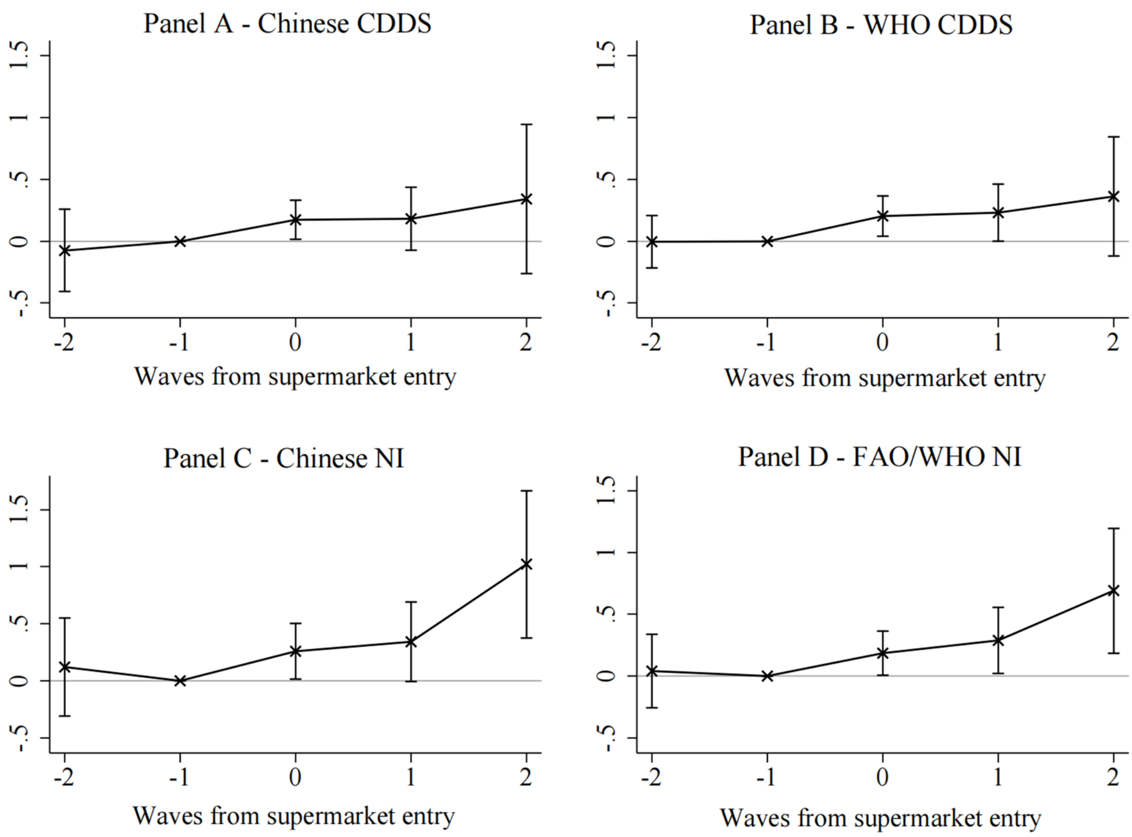

Fig. 2.2 Parallel trend analysis and dynamic treatment effects

Notes: Coefficients, marked by crosses, were obtained with the CDH estimator, including individual and time fixed effects. The error bars indicate 95% confidence intervals. Wave=0 represents the first year that a supermarket was accessible. We use wave=-1 (one period prior to the supermarket entry) as the base year in the regressions.

In a second test, we regress the presence of supermarkets on the dietary indicators in the previous period, before a supermarket was established, as explained in equation (4) above. Results are shown in Tables A13 and A14 in the Appendix, using individual and household fixed effects. In all models, the coefficients for the dietary indicators are very small and insignificant, meaning that reverse causality is unlikely. Dietary patterns do not seem to influence the locations where supermarkets are being established.

In a placebo test, we show that supermarkets have a significantly positive effect on dietary intakes at home, but hardly influence food intakes away from home (Table A15 in the Appendix). These results further add confidence that the estimated effects of supermarkets can be interpreted in a causal sense.

2.4.3 Heterogeneous results

This section analyzes possible heterogeneous effects of supermarkets on different segments of the population. We start by comparing effects by individual characteristics. Fig. 2.3 (panel a) shows the effects of supermarkets for boys and girls. We see mostly positive and significant effects on CDDS and NI for both sexes with very similar coefficients and confidence intervals. While we saw some differences between the dietary quality of boys and girls above, these differences are not reflected in the supermarket effects.

Panel (b) of Fig. 2.3 compares the effects among younger and older children (below and above 6 years). We observe significantly positive effects on CDDS and NI for both groups, with slightly larger point estimates for younger children. This is a welcome finding. While nutritional quality influences body development during all stages of childhood and adolescence, dietary deficiencies during early childhood are particularly severe in terms of their long-term consequences (UNICEF et al., 2021). A possible reason for the somewhat larger positive dietary effects of supermarkets on young children may be that young children eat most of their food at home, whereas school-aged children and adolescents eat some of their food away from home.

In terms of household characteristics, panel (c) of Fig. 2.3 compares the effects of supermarkets for children from low- and high-income households. This classification is based on income differences within each community. We find that supermarkets have statistically significant positive effects on children from low-income households, whereas the effects for children from high-income households are insignificant. These pro-poor effects and can likely be explained by the fact that children from high-income households are nutritionally better off anyway.

In terms of regional characteristics, panel (d) of Fig. 2.3 compares the effects in rural and urban areas. The positive effects of supermarkets on CDDS and NI are all statistically significant in rural areas, but not in urban areas. This is also a welcome finding because children in rural areas suffer more from poor dietary quality than children in urban areas. There are two

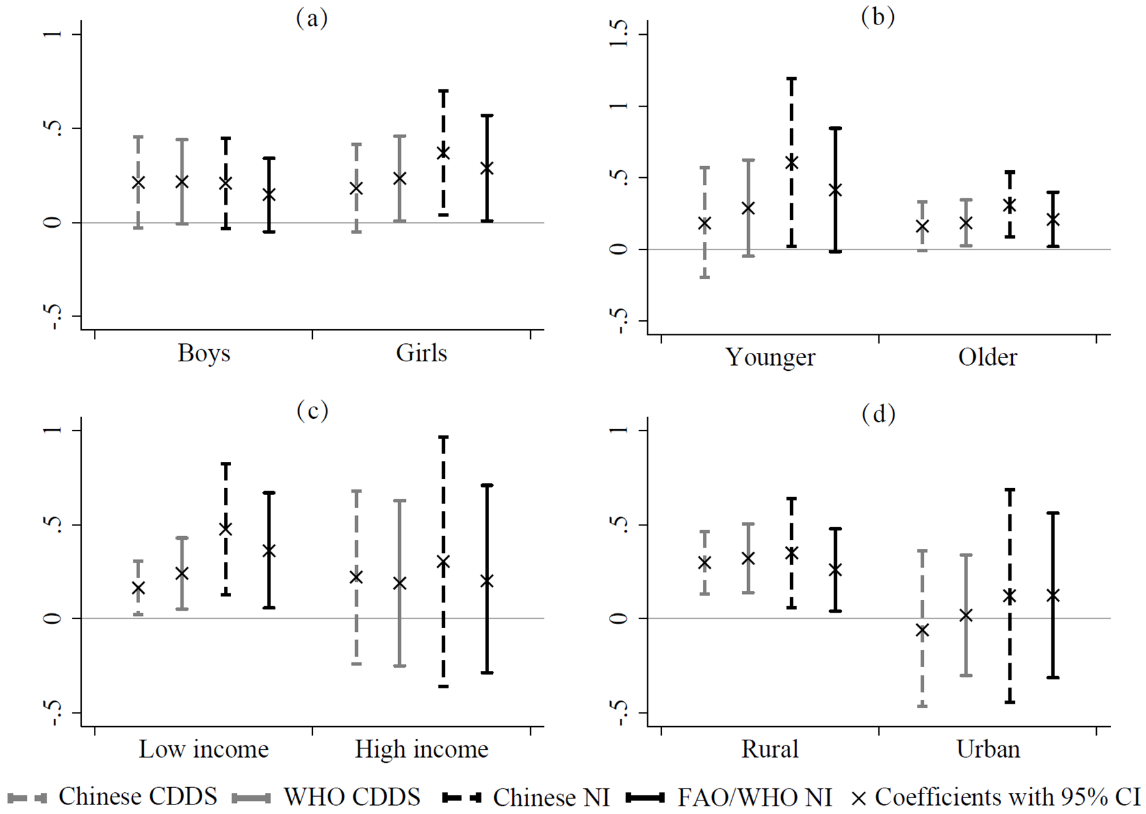

Fig. 2.3 Heterogeneous effects of supermarkets on DDS and NI

Notes: High-income and low-income households are classified by the mean per capita income of all households in each community. Younger and older children are those below and above 6 years, respectively. The numbers of observations in the subsamples are: boys (3,348), girls (2,968), younger (1,781), older (4,535), children from low-income households (4,315), children from high-income households (2,001), rural (3,523), and urban (2,793). Control variables and fixed effects used in all regressions. Results in panels (a), (c), and (d) obtained with CDH regressions; results in panel (b) obtained with TWFE regressions due to insufficient observations in the group of younger children.

possible reasons for the different effects. First, rural households tend to rely more on own and/or local food production, which may be limited in terms of variety and subject to seasonal fluctuation. In such situations, supermarkets can add to the variety and stability of local food supplies. Second, and related to the first point, urban areas tend to have a larger choice of different retailers anyway, including traditional grocery stores, wet markets, and other types of outlets. In such situations, the additional effects of supermarkets may be less relevant.

Another interesting question is whether households with and without a refrigerator experience different effects of supermarkets on child diets. Around 56% of the households in our sample owned a refrigerator during the study period, while the others did not (Table A2).

Owning a refrigerator allows households to purchase and store more fresh and perishable foods, such as vegetables and milk, which may enhance the positive effects of supermarkets on dietary quality. Yet, estimates for the subsamples with and without a refrigerator indicate significantly positive and similar effects of supermarkets in both groups (Table A16 in the Appendix). This is plausible because supermarkets also sell many processed foods with longer shelf lives. Hence, it is not necessary for households to own a refrigerator in order to benefit from supermarkets.[7]

2.4.4 Effects of supermarkets on child nutritional status

We now assess the effects of supermarkets on child nutritional status, using the anthropometric indicators explained above and the CDH estimator. Results are shown in Table 2.5. Access to a supermarket increases child HAZ by 0.085. This is consistent with the dietary findings above. Improved protein and micronutrient intakes contribute to linear growth and reduced rates of child stunting. At the same time, supermarkets do not seem to increase child weight. The effects on BAZ, underweight, overweight, and obesity are all statistically insignificant. These findings suggest that supermarkets have favorable effects on child nutritional status in China, increasing child height without contributing to overweight and obesity.

Table 2.5 Impacts of supermarkets on nutritional status

	HAZ	BAZ	Underweight	Overweight	Obese
	(1)	(2)	(3)	(4)	(5)
Supermarket	0.085*	0.019	-0.009	0.032	-0.010
	(0.044)	(0.062)	(0.016)	(0.020)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	5,805	5,751	5,751	5,751	5,751

Notes: The CDH estimator was used for these regressions. * indicates significance at the 10% level. Standard errors clustered at the community-sex level are shown in parentheses.

7 A related question is whether the entry of supermarkets may possibly influence households' decisions to own a refrigerator. We regress refrigerator ownership on supermarket access and find no significant association (Table A17 in the Appendix). This also eliminates the "bad control variable" problem (Cinelli et al., 2024) that could bias the estimates of supermarket effects, since refrigerator ownership does not seem to be a consequence of supermarket entry.

Heterogeneous effects on child anthropometrics for different subsamples are shown in Table A18 in the Appendix. Consistent with the dietary effects above, the effect of supermarket access on HAZ is larger for young children below the age of 6 years, even though this is not statistically significant. Also consistent with the dietary analysis, we find a positive and statistically significant effect of supermarkets on HAZ among children in rural areas. In none of the subsamples, we see significant effects of supermarkets on BAZ, overweight, and obesity.

2.4.5 Impact pathways

In this subsection, we analyze two possible pathways of how supermarkets may affect child diets and nutrition, namely through a larger supply of food variety and through lowering food prices. We start by looking at food variety. Fig. 2.4 shows the average number of different types of foods sold by the supermarkets in the CHNS sample communities and how this number evolved over time. As can be seen, supermarkets tend to sell a large variety of unhealthy snacks and candies, and this variety increased over time. Yet, supermarkets also sell a variety of fresh vegetables and fruits, and this variety increased at even larger rates over time. Between 2004 and 2011, the variety of fresh vegetables and fruits sold in supermarkets almost doubled. This variety of healthy foods can explain the positive effects on child dietary diversity and nutrient intakes, and also the phenomenon of increasing effects over time.

Next, we look at possible food price changes after the introduction of supermarkets. The CHNS community survey data include prices of various foods from a traditional wet market and a large retail store in or near each community. The large store price is typically the supermarket price when supermarkets are available in a community. These price data are quality-adjusted and hence comparable. When a supermarket enters a community and offers food items at a lower price than traditional markets, it is likely that traditional markets will also adjust their prices to some extent in order to remain competitive. Nevertheless, in a sizeable proportion of the sample communities with a supermarket, we observe food prices in supermarkets to be lower than in traditional markets (Table 2.6). The proportion even increased over time for most food items. A more formal analysis of the price effects of supermarkets would require different data and is beyond the scope of this study. Nevertheless, our findings provide suggestive evidence that supermarkets may have contributed to making nutritious foods more accessible and affordable for Chinese consumers.

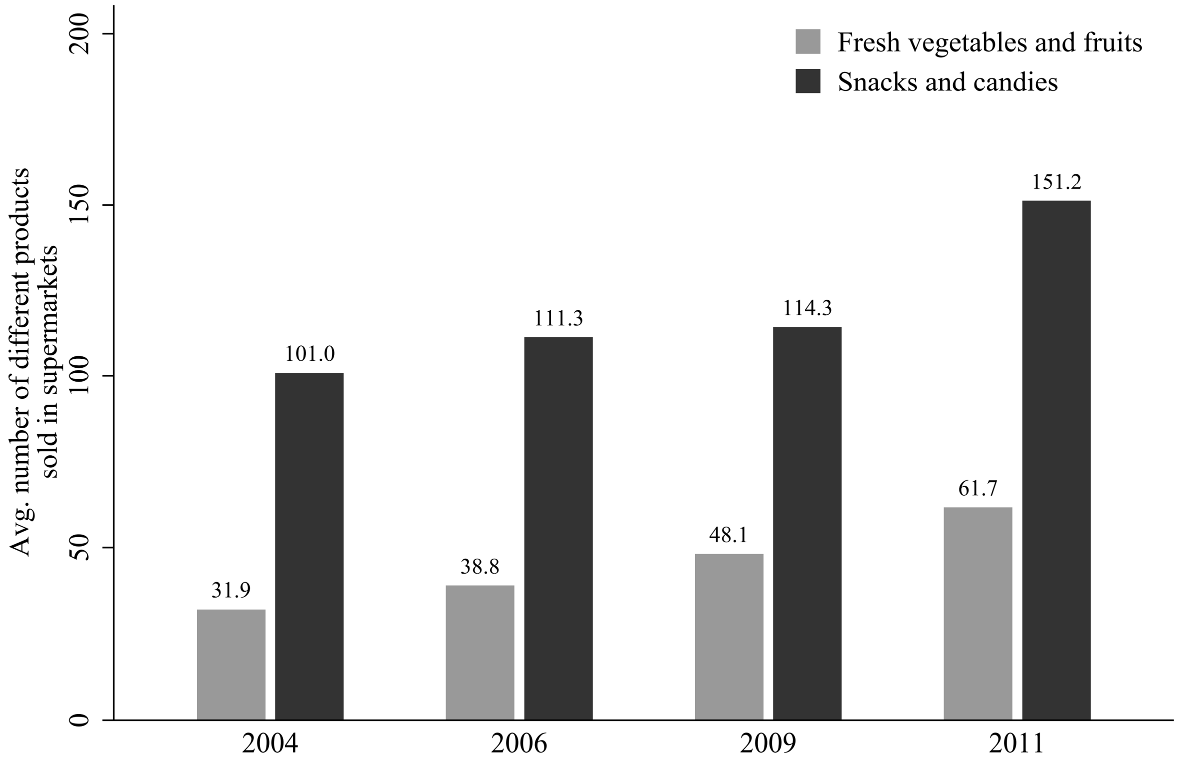

Fig. 2.4 Variety of different types of foods sold in supermarkets in China (2004-2011)

Source: Derived from CHNS community survey.

Table 2.6 Proportion of communities where food prices in supermarkets are lower than in traditional markets

	2004	2006	2009	2011	From 2004 to 2011
Rice	13.64%	5.00%	11.64%	14.46%	+ 0.82%
Wheat flour	5.81%	8.24%	10.24%	10.09%	+ 4.28%
Eggs	33.00%	26.11%	22.39%	30.22%	- 2.78%
Pork	9.62%	19.02%	22.91%	25.53%	+ 15.91%
Chicken	10.64%	13.51%	18.79%	16.27%	+ 5.63%
Vegetables	8.61%	8.78%	19.16%	17.67%	+ 9.06%

Note: Only communities with a supermarket in a particular year are included in price comparisons.

2.5 Conclusion and policy implications

The rapid transformation of agri-food value chains and the growth of supermarkets in many emerging countries is reshaping food environments, which may influence people's food choices, diets, and nutritional outcomes. The nutritional effects of supermarkets in different contexts are not yet well understood. This is particularly true for children, where issues of dietary quality have long-term implications for economic and human development. In this article, we have addressed this knowledge gap by providing the first study analyzing supermarket effects on child nutrition in China, and the first study in any country using panel data with individual-level indicators of child diets.

Using various difference-in-difference estimators and robustness checks, we have addressed a number of potentially relevant sources of endogeneity and therefore prudently interpret our estimates as causal effects. Nevertheless, eliminating all potential sources of bias is difficult with observational data, so that some caution remains warranted. For instance, we cannot rule out with certainty that the locations of supermarket establishment are not endogenously determined based on unobserved factors. Certain government policies supporting the expansion of supermarkets may also promote the transformation of agricultural production and lead to dietary shifts through other mechanisms. Also, traditional retailers and wet markets may react to the entrance of supermarkets in ways that we cannot fully observe and thus influence child diets and nutrition. Follow-up research to analyze specific mechanisms in more detail may therefore be useful.

Nevertheless, some broader conclusions should be in order. Our results suggest that improved access to supermarkets has increased child dietary diversity, nutrient intakes, and height-for-age Z-scores in China. Strikingly, children in rural areas and from low-income households have benefitted more than children from urban areas and higher-income households. We did not find any significant effects of supermarkets on child overweight or obesity, concluding that the expansion of supermarkets had clear positive child nutritional outcomes in China.

We have also explored possible pathways of the observed effects of supermarkets on child nutrition. First, we have shown that supermarkets in China sell both fresh and processed products and thus add to the variety of foods available in local communities. The variety of fresh vegetables and fruits sold in supermarkets increased substantially over time. Second, using community-level data, we have presented suggestive evidence that supermarkets tend to reduce food prices, making healthy diets more accessible and affordable. Greater variety and seasonal stability in local food supplies and lower food prices can explain the observed child nutritional improvements, and also the more pronounced effects in rural areas and low-income households.

Our findings contribute to the international literature on agri-food value chains and the role of food environments for diets and nutrition. One strand of literature, including studies from high-income countries, points out that people's diets are primarily determined by individual factors – such as income, dietary knowledge, and preferences – and not by access to supermarkets or other types of retailers (e.g., Allcott et al., 2019; Zhen, 2021). These studies therefore argue that policies aiming to reduce nutritional issues should focus on raising people's demand and preferences for healthy foods, for instance, through education and/or financial incentives. Another strand of literature from low- and middle-income countries (e.g., Demmler et al., 2018; Debela et al., 2020), but also a few studies from high-income countries (e.g., Zeng et al., 2019), shows that improved access to supermarkets can result in positive nutritional outcomes, suggesting that policies targeted at food environments can help alleviate nutritional problems.

We argue that both strands of literature are not necessarily conflicting. Our results are in line with the second strand of literature, meaning that food environments matter for diets and nutritional outcomes. However, the effects depend on the context. In situations where peoples' access to healthy diets is relatively good anyway, the effects of changes in food environments will likely be smaller than in situations where healthy foods are more difficult to obtain. Of course, in every situation individual factors also play an important role for dietary choices, so policies targeted at improving food environments should never be seen as isolated measures. Improving people's income, nutrition knowledge, and awareness, are important complementary policies to improve diets and nutrition.

Another interesting question is to what extent supermarkets (and other modern retailers) may possibly also contribute to undesirable nutrition and health outcomes. Studies in several low- and middle-income countries show that the rapid spread of supermarkets leads to more consumption of processed foods and contributes to overweight and obesity among adults (Asfaw, 2008; Kimenju et al., 2015; Demmler et al., 2018; Otterbach et al., 2021). Nevertheless, a few studies also show improvements in dietary diversity and nutrient intakes (Rischke et al., 2015; Khonje et al. 2020). For children, the evidence is more patchy even though some studies with data from Africa suggest that supermarkets help reduce child nutritional deficiencies and stunting (Debela et al., 2020; Khonje et al., 2020). This is in line with our findings for China, even though the earlier research in Africa focuses only on urban areas, whereas here we have looked at both urban and rural areas. In any case, the notion that supermarkets and other modern retailers would always contribute to lower-quality diets is incorrect. Our results from China demonstrate that supermarkets can help improve people's access to healthy foods and thus contribute to improved diets and nutrition.

Overall, the nutritional effects will vary also depending on what types of foods are sold by supermarkets at what prices, which also has implications for the transformation of agri-food value chains. In China, supermarkets do not only sell ultra-processed foods but also a variety of fresh and nutritious foods. This is partly related to local consumer preferences but likely also to well-developed road infrastructure in rural and urban areas, facilitating the logistics for fresh food supplies. This may be much more difficult in rural regions of Africa, where the road infrastructure is typically less developed. A general policy implication is that private market developments and food environment trends can contribute to favorable health and nutrition outcomes provided that proper public infrastructure is in place. Some regulation to reduce the sales of ultra-processed unhealthy foods may also be useful to improve nutritional outcomes in certain situations.

CHAPTER 3

Supermarkets Benefit Women by Reducing Time Spent on Unpaid Housework

Abstract

Women worldwide shoulder a disproportionate share of unpaid housework, with food shopping and cooking often representing the largest burden. Reducing time spent on these tasks is essential to closing gender gaps, but comes with concerns about worsening dietary quality. We explore potential trade-offs by analyzing effects of supermarkets on women's time use and dietary outcomes using nationwide longitudinal data from China. We find that supermarkets reduce women's shopping and cooking time by over 20%. Key mechanisms include the availability of diverse foods under one roof and a certain shift from unprocessed to moderately processed foods. Nutritional goals are not sacrificed; in fact, dietary diversity and nutrient density are enhanced, especially among those with lower-quality diets. The time savings also entail higher female participation in paid work. While the effects depend on the context, our findings highlight the potential of supermarkets to empower women by reducing the burden of unpaid work.

Keywords: sustainability, nutrition, gender equity, time use, supermarkets

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This chapter is co-authored by Lukas Kornher and Matin Qaim. Zhen Liu was primarily responsible for the conceptualization, methodological design, data analysis, and drafting and revising of the manuscript. Lukas Kornher contributed to conceptualization, methodological refinement, and manuscript review. Matin Qaim provided conceptual guidance, supervised the research process, and contributed to the review and revision of the manuscript.

3.1 Introduction

The widely observed gender gap in time allocation remains a critical barrier to women's empowerment (Pal et al., 2022). Globally, women perform around three-quarters of all unpaid household chores and care work (Riddell et al., 2024). While not priced and traded in markets, the value of women's unpaid work is estimated in a range of 10-39% of global gross domestic product (GDP) (UN, 2016). Food shopping and cooking are particularly time-intensive tasks. The average woman spends about 500 hours each year on preparing 486 meals (Gallup & Cookpad, 2020; Wolfson et al., 2021). In many low- and middle-income countries (LMICs), shopping and cooking account for over 30% of women's household chores (Ferrant et al., 2014; Singh & Pattanaik, 2020). Prolonged exposure to kitchen environments may harm women's health (Ervin et al., 2023; McMunn, 2023; Seedat & Rondon, 2021), apart from provoking trade-offs between unpaid work, paid work, and leisure (Carmichael et al., 2023; Sullivan, 2019). Time constraints can also reinforce social norms that prioritize women's responsibility for household chores, perpetuating gender inequality across generations (Jayachandran, 2021). A heavy time burden through unpaid housework does not only hinder women's empowerment but also impedes economic development by misallocating female labor and talent (Dinkelman & Ngai, 2022; Hyde et al., 2020).

Changing gender roles is a long-term process that can be supported by time-saving innovations, including new technologies as well as institutional advancements. Modern food retailers, particularly supermarkets, offer a potential avenue to reduce women's time required for food shopping and cooking. Unlike traditional retailers, such as wet markets and street hawkers, supermarkets offer a larger variety of foods under one roof (Hawkes, 2008), streamlining the shopping process and thus reducing shopping time. Also, supermarkets offer more processed foods with longer shelf lives (Demmler et al., 2018; Rischke et al., 2015), thus facilitating household storage and reducing shopping frequency. The consumption of processed foods can save cooking time as well. Even for fresh foods, purchasing from supermarkets can make cooking less laborious because supermarkets often sell products that are cleaned and have inedible parts already removed (Bogard et al., 2024).

The time potentially saved through supermarkets could improve women's well-being by reducing health risks (Sun et al., 2023; Yu et al., 2023), and by freeing up time for paid work or leisure, which could increase income (Dinkelman & Ngai, 2022) and alleviate stress from repetitive household chores (Seedat & Rondon, 2021). Nevertheless, such time savings may come with unintended side-effects, particularly regarding dietary quality. While supermarkets can improve access to food (Debela et al., 2020; Liu et al., 2024; Zeng et al., 2019), they may also increase the consumption of processed and ultra-processed products, thus raising risks of obesity and other non-communicable diseases (Demmler et al., 2018; Otterbach et al., 2021). In contrast, without supermarkets, women may spend more time on shopping and cooking but they and their families may consume more fresh and nutritious foods (Monsivais et al., 2014; Takeshima et al., 2022). Here, we analyze effects of supermarkets on women's time use and potential trade-offs with dietary quality and nutrition.

Issues around gender gaps in unpaid housework, time-saving innovations, and dietary quality are globally relevant, but the role of supermarkets in this connection is not yet sufficiently understood. In fact, we are not aware of any studies that analyze effects of supermarkets on women's time use with quantitative data, neither in high-income countries, where supermarkets have already spread since the 1960s (Qaim, 2017), nor in LMICs, where the growth of supermarkets has started more recently (Barrett et al., 2022). We use data from China, the country with the fastest supermarket growth over the past two decades. Observing how women in China allocate time and how diets have changed with the entry of supermarkets is interesting as such, but also offers some insights into what likely happened in the past or is happening at present in other parts of the world.

We start by illustrating gendered time allocation in China and its interplay with supermarket diffusion. Then, we estimate the impact of supermarkets on women's time spent on food shopping and cooking using micro-level data. We use difference-in-differences (DID) regression models to identify effects of supermarket access on women's time use and also explore the underlying mechanisms. In addition, we estimate effects on various indicators of dietary quality, nutritional outcome, and women's reallocation of time across unpaid and paid activities.

3.2 Data and variables

3.2.1 Data source

The micro-level data used for the analysis of supermarket effects are also from the China Health and Nutrition Survey (CHNS), a joint project by the Chinese Centers for Disease Control and Prevention and the University of North Carolina at Chapel Hill. This longitudinal survey tracks the dynamics of peoples' dietary intake, their health status, and other socioeconomic characteristics in approximately 7,200 households and 30,000 individuals randomly selected from 15 provinces and municipal cities (rural and urban areas) in China.

CHNS also contains information on neighborhood infrastructure and services, including supermarket proximity. The survey has been conducted over ten waves since 1989, but only four waves (2004, 2006, 2009, 2011) simultaneously collected data on women's food shopping and cooking time, supermarket proximity, and dietary intake, so in the regressions we only use data from these four waves. Women still in school, pregnant, or sick and hospitalized during the survey period are excluded, as these conditions can change time allocation considerably. Our relevant sample includes 5,822 complete observations of women aged 18-79 years who reported spending time on food shopping or cooking during at least one of the four survey waves.

3.2.2 Definition of supermarket access

The key explanatory variable used in this research is access to supermarkets, which is a dummy indicating whether or not there is a supermarket located within 5 kilometers from the household. Supermarkets are defined as large, self-service food stores that sell a substantially wider variety of foods than traditional food stores. Supermarket information was obtained from a person familiar with local affairs, often the community head, by asking, "*How many supermarkets or hypermarkets are within 5 kilometers from this village/neighborhood?*" and "*How far is the supermarket where this village/neighborhood's residents often shop?*" Given that communities in China are typically quite compact, the recorded indicators can be seen as proxies for each household's access to supermarkets. We generate a dummy for supermarket access, instead of using the number of supermarkets or the physical distance to supermarkets, as the survey did not conduct field verification to check the accuracy of the reported numbers and exact locations of supermarkets. CHNS also collected food prices from a supermarket within 5 km where residents of a particular community frequently shop, allowing us to cross-check and thus increase data accuracy.

3.2.3 Definition of women's time use variables

Key outcome variables in this study are women's time spent on food shopping and cooking per day (unit: minutes). Data for these variables in CHNS were collected by asking women: "*Did you buy food for your household during the past week? If yes, how much time (minutes) did you spend per day, on average, including the time for transportation?*" and "*Did you prepare and* *cook food for your household during the past week? If yes, how much time (minutes) did you spend per day, on average?*". Those respondents who answered "No" were assigned a minute value of 0. In the regression analysis, we use the logarithm of these two time-use variables because their distribution is skewed toward zero.

To evaluate time reallocation, we consider four additional activities: (1) paid work, (2) other unpaid household chores (other than shopping and cooking), (3) leisure, and (4) sleep. Paid work is defined as all income-generating activities, including employment, self-employment, and household agricultural production. Other unpaid household chores include mainly washing and cleaning. Leisure includes sedentary, non-income-generating activities, such as watching television, chatting, reading, and similar pastimes. We calculate the time spent on each of these activities separately. For paid work, we additionally create a dummy variable that takes a value of one if a woman reported to have spent at least 30 minutes per week on paid work.

3.2.4 Definition of diet and nutrition indicators

To study the effects of supermarkets on diets and nutrition, we use individual-level diet and anthropometric data. Individual dietary data were collected through 24-hour dietary recalls repeated over three consecutive days, recording intakes of over 1,500 coded foods consumed both at home and away from home, across main meals and snacks. Individual intake data for condiments (e.g., salt, edible oil, soy sauce, vinegar) are not available. Therefore, following Huang & Tian (2019), we estimate condiment consumption using the household food inventory change dataset from CHNS. This dataset records total household consumption and the number of times each person ate at home during the survey period. We calculate a weighted average based on the number of meals eaten at home per person per day to estimate individual condiment intake. Using the China Food Composition Tables (CFCT) (2002 and 2004 Editions, see https://www.chinanutri.cn/yyjkzxpt/yyjkkpzx/hdjl/201501/t20150115_109857.html), each food item consumed is identified, and energy and nutrient intakes are calculated by multiplying the average daily quantity of the edible proportion of each food item by the respective nutritional contents.

We assess individual dietary quality using three complementary indicators for dietary diversity, dietary balance, and dietary nutrient density, which together provide a comprehensive picture. First, the individual Dietary Diversity Score (DDS), which is commonly used in the existing literature to measure dietary quality, is calculated according to the Chinese Food Guide

Pagoda 2022 (CFGP 2022). For this, all consumed food items are categorized into nine food groups, namely (1) grains, (2) roots and tubers, (3) legumes and nuts, (4) vegetables, (5) fruits, (6) meat and poultry, (7) eggs, (8) aquatic products, and (9) milk and its products. The average daily number of food groups consumed over the three-day period represents the DDS, which can take values between 0 and 9, with higher values indicating higher dietary quality.

Second, we calculate the Chinese Food Pagoda Score (CFPS) to measures the alignment with the recommended consumption quantity of CFGP 2022 (http://dg.cnsoc.org/article/04/RMAbPdrjQ6CGWTwmo62hQg.html), drawing on a methodology proposed in previous research (Huang & Tian, 2019). CFGP 2022 provides recommended intake ranges for eight food groups: (1) starchy staple foods (grains, roots, and tubers combined), (2) vegetables, (3) fruits, (4) animal-sourced foods other than milk (meat, poultry, aquatic products, and egg combined), (5) milk and its products, (6) legumes and nuts, (7) edible oils, and (8) salt. The CFPS is calculated as the sum of sub-scores assigned to each food group. For the sub-score, a value of "1" is given if an individual's intake falls within the recommended range, "0.5" if the intake is not within the recommended range but is higher than 50% of the lower bound and lower than 150% of the upper bound, and "0" if the intake is below 50% of the lower bound or above 150% of the upper bound. An exception is the score for salt, which receives a "0" if the intake exceeds the upper limit. See Table B1 in the Appendix for details. A greater CFPS suggests a more balanced and healthier diet. We use the average CFPS of individuals over the three-day period in each survey wave in the regressions.

Third, we construct the Dietary Nutrient Density Score (DNDS) to assess dietary quality based on nutrient content. The first step is to calculate the Nutrient Rich Food (NRF) Index of each food item, a commonly used measure of nutritional quality that has been validated using data from both high-income countries and LMICs (Drewnowski, 2010; Fulgoni et al., 2009; Sluik et al., 2015; Zhai et al., 2022). The index incorporates nine nutrients generally beneficial to human health (i.e., protein, fiber, vitamins A, C, and E, calcium, iron, potassium, and magnesium) and one nutrient (sodium) recommended for limited intake. Added sugar and saturated fat are also often considered as nutrients to be limited but are excluded here, as their content data are not available in the CFCT. The algorithm of calculating NRF9.1 is:

$$NRF9.1_k = \sum_{v=1}^{9}\left(\frac{Nutrient_v}{RDI_v} \times 100\right) - \left(\frac{Sodium}{MDI} \times 100\right) \tag{1}$$

in which $Nutrient_v$ is the content of nutrient v in a 100-kcal edible portion, and $Sodium$

is the content of sodium in a 100-kcal edible portion of food item k. RDI_v and MDI represent the recommended daily intake for nutrient v and the recommended maximum daily intake for sodium, respectively, as proposed by the Chinese Nutrition Society (https://www.chinanutri.cn/xxzy/xxzydybgsj/201506/t20150603_115510.html). Therefore, the first term in equation (1) represents the percentage of the recommended intake of nutrient v of the consumed food item k, while the second term accounts for the percentage of the upper limit for sodium. Next, DNDS is calculated as the energy-weighted average of the NRF9.1 scores of all n foods consumed by individual i:

$$DNDS_i = \frac{\sum_{k=1}^{n}(NRF9.1_k \times Energy\ Intake_k)}{\sum_{k=1}^{n} Energy\ Intake_k} \tag{2}$$

The energy contribution of each food item to total dietary intake serves as the weighting factor, ensuring that foods providing more energy have a proportionately larger influence on the final score. In the regressions, we use the average DNDS of individuals over the three-day period.

Anthropometric variables to assess nutritional outcomes include the body mass index (BMI) and two dummy variables indicating overweight and obesity. Adult BMI is calculated as the body weight (in kilograms) divided by the square of the height (in meters). Overweight is defined as a BMI ≥ 25, and obesity as a BMI ≥ 30, in accordance with World Health Organization guidelines (https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight).

3.3 Econometric approaches

3.3.1 Regression models

To assess the impacts of supermarkets on the different outcome variables, we exploit the variation in the access to supermarkets across communities and over time in a difference-in-differences (DID) model of the following type:

$$Y_{ijt} = \beta_0 + \beta_1 Supermarket_{jt} + \beta_2 X_{ijt} + \theta_i + T_t + R_t + \varepsilon_{ijt} \tag{3}$$

In the baseline regressions, Y_{ijt} represents the respective outcome variable of interest (see above) for individual i in community j and year t. $Supermarket_{jt}$ is the key explanatory variable (see above). To control for confounding factors, we include additional explanatory variables (X_{ijt}) in equation (3) that may be jointly correlated with supermarket access and the outcome variables, covering individual, household, and community-level characteristics. Individual characteristics include women's age and age squared, activity level, and dietary knowledge. Household characteristics include family size, per capita household income, household agricultural production diversity, and ownerships of assets potentially affecting food purchasing (i.e., motorcycle and car). Community-level characteristics include access to restaurants and traditional food stores like wet markets. Detailed variable definitions and descriptive statistics are shown in Table B2 in the Appendix.

The panel structure of our data enables us to include fixed effects to alleviate confounding influences from unobserved heterogeneity. Individual fixed effects (θ_i) account for unobserved time-invariant factors, such as individual dietary preferences shaped during childhood, religious beliefs, chronic diseases, local dietary culture, and local agricultural products. Year fixed effects (T_t) capture common temporal shocks affecting all households, such as changes in food and economic policies. Our most comprehensive specification deals with unobserved factors that vary across regions and over time, such as regional price fluctuations for certain food products, through the inclusion of province-by-year fixed effects (R_t). Standard errors are clustered at the community level to accommodate for intra-community correlation among households.

Despite the use of several control variables and various fixed effects, concerns may persist about overestimating the time-saving effects of supermarkets due to possible omitted variables correlated with supermarket diffusion. For instance, continued economic growth may contribute to the observed trend of declining cooking time by increasing the opportunity cost of women's time for unpaid household chores. Supermarkets might not be necessary for this if traditional markets and grocery stores are available. Besides, improvements in infrastructure, such as electricity, may encourage the use of modern kitchen appliances that can also reduce cooking time. To address these concerns, we further control for local economic activity (an aggregated index provided by CHNS, reflecting typical daily wages for ordinary male workers and the percentage of the population in off-farm work) and household ownership of a fridge, microwave, and pressure cooker.

We are particularly interested in the coefficient β_1 in equation (3), which represents the average treatment effect on the treated (ATT). It measures the average difference in potential outcomes between individuals experiencing the exposure to supermarkets within 5 km of their home and those without such access. In our setting, where supermarkets enter different areas at different points in time (staggered treatment), estimates from the standard two-way fixed effects model are likely to be biased by "bad" treatment combinations due to heterogeneity in treatment status (Callaway & Sant Anna, 2021; de Chaisemartin & D Haultfœuille, 2023b; Goodman-Bacon, 2021). To address this issue, we apply a new DID estimator with multiple time periods (Callaway & Sant Anna, 2021), which is robust to treatment timing and treatment effect heterogeneity.

The basic identification assumption of this DID model with multiple time periods is that the average outcomes for the treatment group and the never-treated group would have followed parallel trends in the absence of supermarkets. In our event study, when looking at the dynamic effects of supermarkets, we examine the parallel trends assumption. If the coefficients in the survey wave prior to the entry of supermarkets are all close to zero and statistically insignificant, this means that the parallel trends assumption is not rejected. We also estimate β_1 by comparing the average outcomes for the treatment group and the not-yet-treated group, and the results are consistent.

3.3.2 Analysis of impact mechanisms

We also aim to examine the mechanisms through which supermarkets may influence women's shopping and cooking time. First, we assume that supermarkets can meet a broad range of food needs under one roof, thereby reducing shopping time. We analyze whether this assumption is realistic by looking at the food variety supermarkets offer. CHNS collects information on the variety of foods sold in supermarkets by asking community heads two key questions, "*How many different types of fresh vegetables and fruits are available in the supermarket where residents in this neighborhood/village often shop?*" and "*How many different types of snack foods and candy are available in the supermarket where residents in this neighborhood/village often shop?*" We use the number of different fresh vegetables and fruits thus recorded as a proxy for the variety of fresh foods, and the number of snack foods and candy as a proxy for processed foods.

However, an increase in food variety does not automatically lead to greater consumer reliance on supermarkets and reduced shopping time. We therefore also analyze people's shopping preferences and behaviors. CHNS collects useful information for five food categories (i.e., grains, fruits, vegetables, snack foods, and packaged/instant foods) by asking community heads, "*If this particular food item is available from supermarkets, are residents in this neighborhood/village less likely to purchase it from traditional free markets? 1 for yes, otherwise 0.*"

Second, we expect that supermarkets lead to an increase in the consumption of processed foods (Demmler et al., 2018; Hawkes, 2008; Rischke et al., 2015), which would reduce the time needed for shopping (lower frequency) and cooking. To analyze this, we partition people's energy and macronutrient intakes (i.e., protein, fat, and carbohydrates) into sources from unprocessed, moderately processed, and highly processed foods. There is no single food classification system that applies to all countries. We follow three principles that are commonly highlighted as important criteria from a health perspective (Barrett et al., 2024; de Araújo et al., 2022), to sort foods into the unprocessed, moderately processed, and highly processed categories, namely: (1) Retention of inherent properties: whether the food retains the recognizable characteristics of its original plant or animal source. (2) Extent of added industrial ingredients: the degree to which sugars, fats, salt, or other additives are included. (3) Purpose of processing: whether processing is intended to ensure safety and suitability for household purchase and consumption or to enhance taste and visual appeal. For a detailed definition of the processing categories and examples, refer to Table B4 in the Appendix.

3.4 Results

3.4.1 Trends in supermarket growth, women's time use, and diets in China

Women in China undertake 72% of all household unpaid work (Fig. B1a in the Appendix), with meal preparation (incl. shopping and cooking) being the most time-consuming task. On average, women spend 1 hour and 24 minutes per day preparing meals (Fig. B1b), accounting for 37% of their total unpaid work, surpassing even care work (33%). Over the past three decades, the time spent on meal preparation has decreased by about 40%, primarily due to a reduction in cooking time—from about 115 minutes per day in the early-1990s to under 1 hour by the 2010s (Fig. 3.1a).

While total meal preparation time has decreased, food shopping time has slowly increased (Fig. 3.1a). This trend is likely related to structural changes and policy reforms in China since the early-1980s. The role of food sourced from own household production has declined, while markets for food producers and consumers were liberalized. Before these policy reforms, farmers could only sell produce to state institutions at fixed prices, and urban residents relied on food rations. These controls were gradually lifted in the 1980s, leading to income growth and more diversity in food markets (Huang & Rozelle, 2006; Lin, 1997).

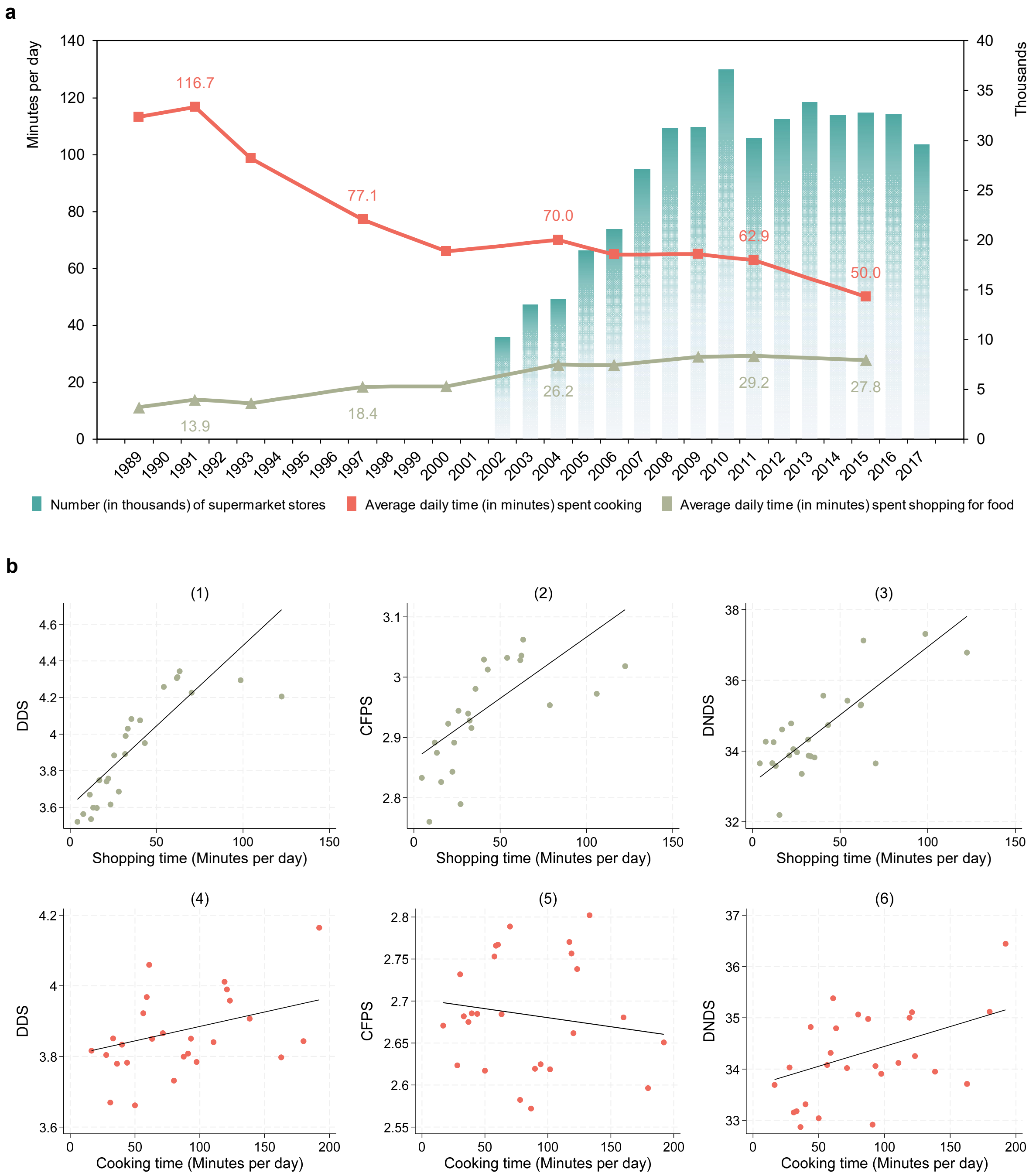


Fig. 3.1 Trends in supermarket expansion, women's time use, and diets in China

Notes: **a**, Changes in women's average time spent on food shopping and cooking (left axis), and number of supermarket stores (right axis) in China. **b**, Binned scatterplots between women's time use and dietary quality indicators of household members (both women and men). Supermarket data are from the CEIC China database (https://www.ceicdata.com/en/china/supermarket), and the data for time use and diets are from the CHNS.

Supermarkets began to develop in the early-2000s, when China abolished most restrictions on food trading and retailing. Fig. 3.1a illustrates potential linkages between supermarkets and women's time use. Between 2004 and 2015, the number of supermarket stores more than doubled and remained above 30 thousand since then. During this period, women's cooking time decreased by 27%, or around 20 minutes per day. Shopping time remained almost unchanged between 2004 and 2015. However, comparing women with and without access to supermarkets (Fig. B2 in the Appendix) reveals that shopping time decreased for women with supermarket access, while it increased for those without, implying a negative relationship between supermarket access and shopping time.

Nevertheless, these trends should be interpreted cautiously, as they do not necessarily reflect causal effects. Between the late-1980s and early-2000s, supermarkets hardly existed in China, even though women's cooking time decreased considerably. This indicates that factors other than supermarkets also contributed to the observed changes in time use. Table B5 in the Appendix presents data on infrastructure, employment, and food-related innovations from 1989 to 2011. These data show increases in road infrastructure, electricity, clean water supply, non-agricultural employment, and access to traditional food markets both before and after the entry of supermarkets. Moreover, refrigerators, microwaves, and other modern kitchen appliances became more popular over time. These trends likely also reduced shopping and cooking time. Below, we use regression models controlling for such confounding factors to identify the net effects of supermarkets on women's time use.

For evaluating dietary consequences of supermarkets, we use three measures of dietary quality (Methods): the Dietary Diversity Score (DDS), which counts the number of food groups consumed; the Chinese Food Pagoda Score (CFPS), which evaluates the alignment of food intake with recommended quantities; and the Dietary Nutrient Density Score (DNDS), which assesses the content of health-promoting nutrients in diets. Panels 1-3 of Fig. 3.1b show a strong positive correlation between women's shopping time and dietary quality. The relationship between cooking time and dietary quality is more ambiguous (Panels 4-6 of Fig. 3.1b). These scatter plots partly support the conventional wisdom that meal preparation time influences dietary quality but also highlight the need to distinguish between shopping and cooking time.

3.4.2 Time-saving effects of supermarkets

We use DID regression models to estimate the average treatment effect of supermarkets on different outcomes, and Fig. 3.2a summarizes results across different model specifications.

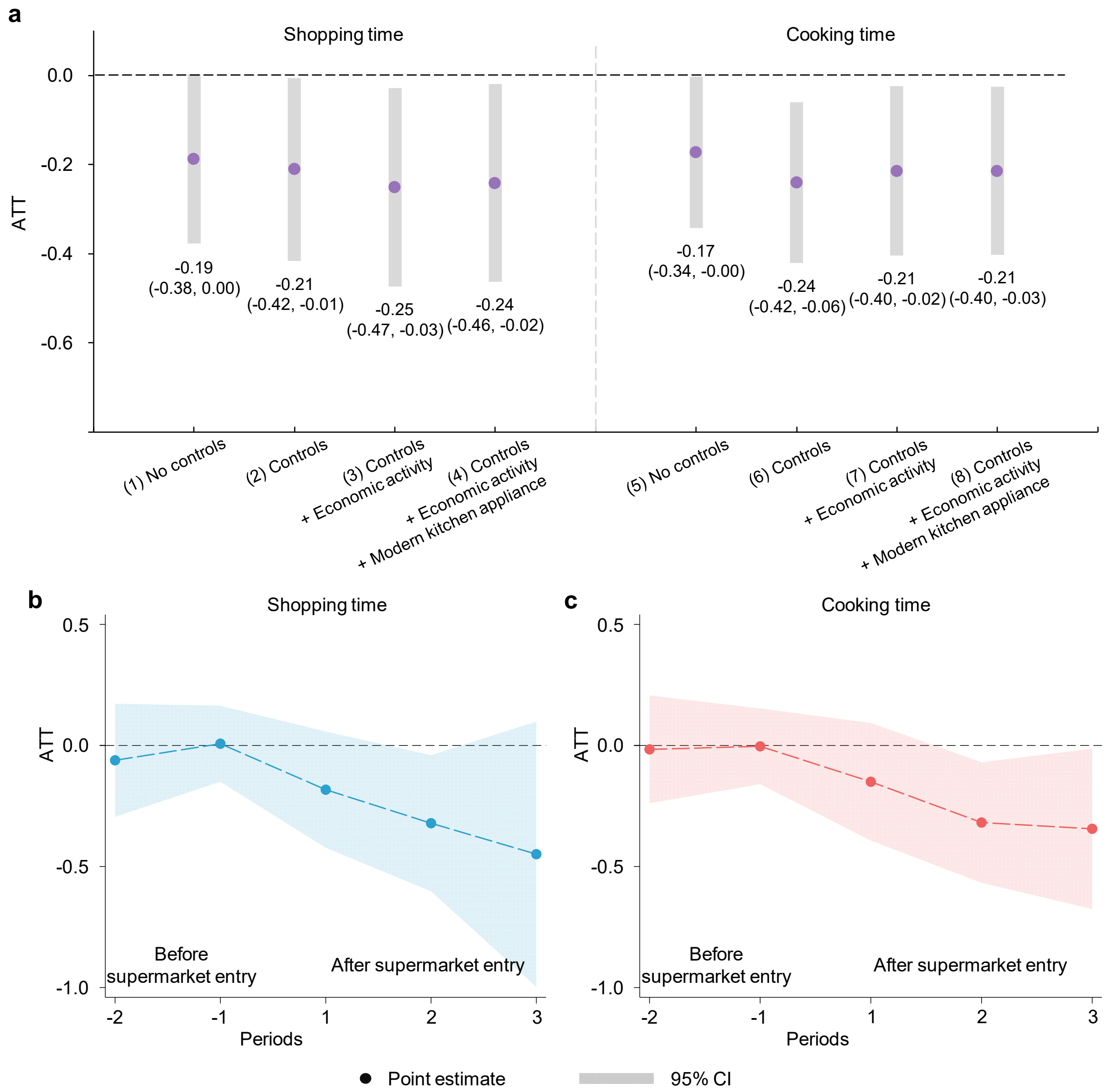


Fig. 3.2 Impacts of supermarket on women's time used for food shopping and cooking in China

Notes: **a**, Average treatment effect on the treated (ATT) estimated using DID models with varying control variables. **b,c**, Parallel trends assumption tests and effects of supermarkets over time. Model details are explained in Methods. Coefficients, which can be interpreted in percentage terms, are shown with 95% confidence intervals (CI) in terms of shaded areas. In **a**, point estimates are also shown numerically with 95% CI in parentheses. In **a**, models (1) and (5) do not use control variables, while models (2) and (6) include controls as shown in equation (3) in Methods. In models (3)-(4) and (7)-(8), additional confounders measuring local economic activity and household ownership of modern kitchen appliances are sequentially controlled for to perform robustness checks. In **b** and **c**, the models include both the controls shown in equation (2) and potential confounders (i.e., local economic activity and household ownership of modern kitchen appliances). Number of observations for analyzing shopping time is 5,576, while for cooking time it is 5,765.

Models (1) and (5) do not include control variables, whereas models (2) and (6) include control variables at individual, household, and community levels (Methods). Models (3)-(4) and (7)-(8) further control for local economic activity and households' ownership of modern kitchen appliances. Across all specifications, supermarket access is negatively associated with women's shopping and cooking time (p-value < 0.05). We focus on models (4) and (8), which include all confounders, for interpretation. Specifically, supermarket access reduces women's shopping time by 24% (approximately 6 minutes per day) and cooking time by 21% (approximately 17 minutes per day). Notably, the reduction in cooking time exceeds the average decrease of 7 minutes observed across all women in China from 2004 to 2011 (Fig. 3.1a).

The parallel trends assumption, a critical requirement for DID models, is tested using an event study approach. Note that supermarkets were not introduced everywhere at the same time. The coefficients for periods prior to the entry of supermarkets are all close to zero and statistically insignificant (Fig. 3.2b,c), confirming the validity of the parallel trends assumption. Fig. 3.2b,c also show that the time-saving effects of supermarkets tend to increase: by the third period after supermarket entry, women's shopping and cooking times are reduced by as much as 45% (11 minutes per day) and 34% (27 minutes per day), respectively. These results suggest the sustained capacity of supermarkets to alleviate women's unpaid work burden.

To assess robustness, we perform two additional tests. First, about 15% of the households in our sample are multigenerational, with two or more adult women involved in food shopping or cooking. Capturing data from multiple women in the same households may possibly lead to a certain bias. To address this concern, we restrict the sample to those women in each household who spend the most time on shopping and cooking (i.e., one woman per household). The results remain unchanged (Table B6 in the Appendix). Second, although it is plausible that supermarkets reduce women's time spent on shopping and cooking, it is possible that some of this time is shifted to men. For example, processed foods from supermarkets may make cooking easier and encourage men's involvement. We examine the effects of supermarkets on men's time spent on shopping and cooking and find no significant effects (Table B6). These tests confirm the robustness of our main results.

3.4.3 Impact mechanisms

Supermarkets may reduce shopping time by meeting consumers' food needs under one roof. Fig. 3.3a illustrates that the average number of both unprocessed and processed foods offered in supermarket in China increased substantially between 2004 and 2011. However, an increase

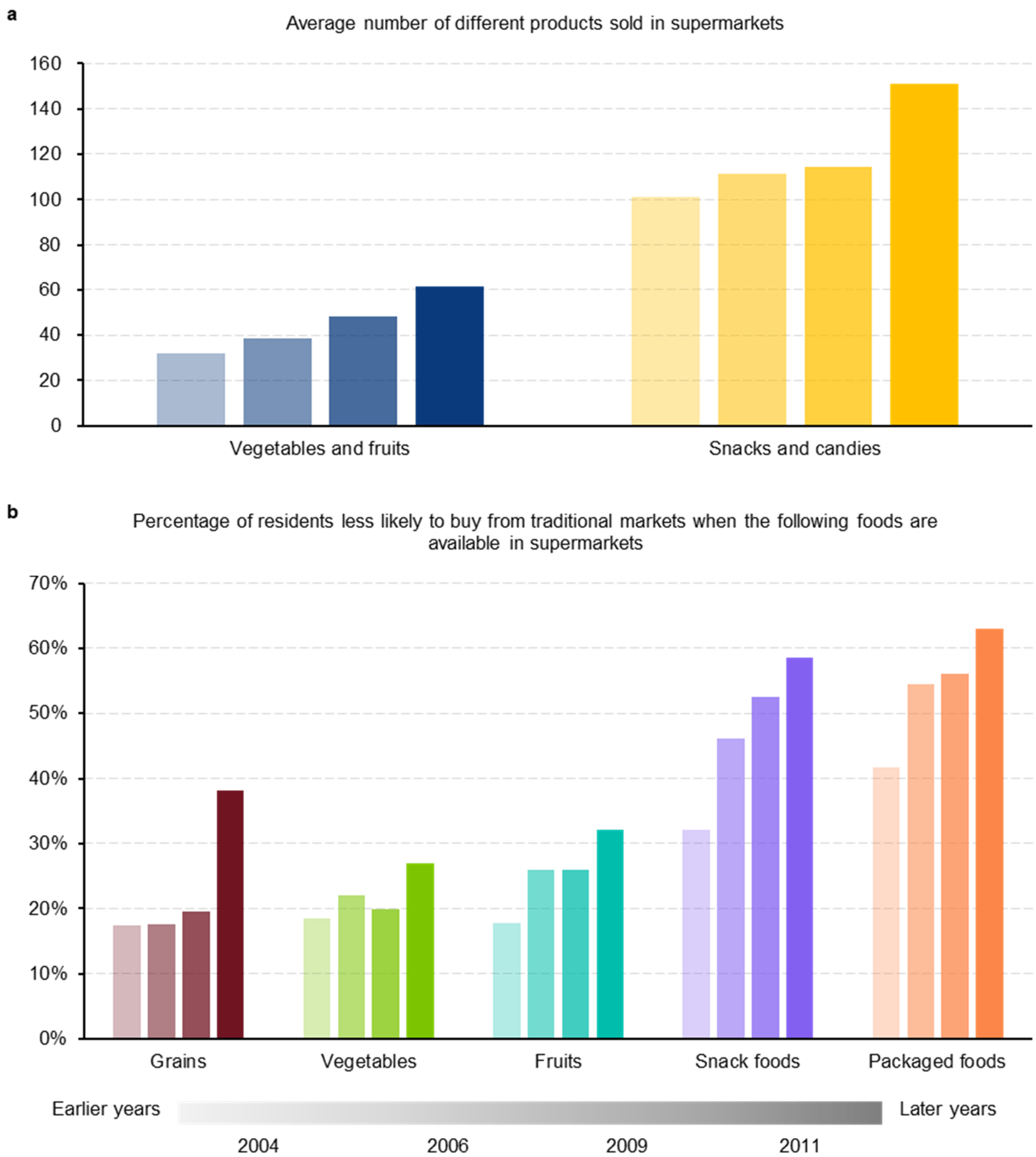


Fig. 3.3 Descriptive analysis of the growth in the variety of food products offered in supermarkets and changing shopping preferences in China in 2004–2011

Notes: **a**, Average number of unprocessed foods (using vegetables and fruits as a proxy) and processed foods (using snacks and candies as a proxy) available in supermarkets in China. **b**, People's shopping preferences across different food groups. Data are from the CHNS.

in food variety does not automatically lead to greater consumer reliance on supermarkets and reduced shopping time. To obtain further insights, we examine shopping preferences for various food groups and find that the share of consumers preferring supermarkets over traditional markets increased over time, provided that the particular foods are sold in supermarkets (Fig. 3.3b). This is especially true for packaged foods, but increasingly also for grains, vegetables, and fruits. Convenience seems to be a key factor for the popularity of supermarkets among food consumers (Bogard et al., 2024).

Next, we investigate changes in dietary composition that could explain the observed reduction in shopping and cooking time through supermarkets. A likely mechanism is through higher consumption of processed foods, which are less perishable and require less cooking time than unprocessed foods. To measure the role of different food types in people's diets, we calculate energy and macronutrient intakes (i.e., protein, fat, and carbohydrates) from the edible portions of consumed unprocessed, moderately processed, and highly processed foods (Methods). We distinguish between moderately processed and highly processed foods because they differ in terms of nutrient contents and healthfulness. Fig. 3.4 shows results from DID regression models, revealing that supermarkets tend to reduce intakes of unprocessed foods and increase intakes of moderately processed but not highly processed foods. More specifically, supermarkets reduce energy intake from unprocessed foods by about 220 kcal per day (Fig. 3.4b), while increasing intake from moderately processed foods by about 60 kcal per day (Fig. 3.4c). These effects increase over time in absolute terms. Similar patterns are also observed for protein, fat, and carbohydrates (Fig. 3.4f-h,j-l,n-p). These results support the hypothesis that supermarkets reduce women's cooking time through a certain shift from unprocessed to moderately processed foods.

3.4.4 Impacts on dietary quality and nutritional outcomes

Reductions in shopping and cooking time and a shift towards more processed foods may also influence dietary quality and overall nutrient intakes, which we explore now in more detail. We start by looking at the effects of supermarkets on total energy and macronutrient intakes per capita, as shown in Fig. 3.4a,e,i,m. Supermarkets significantly reduce total energy and carbohydrate intakes. For protein intake, no significant effect is observed, whereas for fat intake, supermarkets seem to have an increasing impact. Lower energy intake might cause problems in undernourished population groups, but further subgroup analysis shows that a significant reduction is only observed among those with sufficient energy supplies (Table B7 in the

Appendix). The increase in fat and reduction in carbohydrate intakes result in a higher proportion of energy from fat and an increase in the likelihood of exceeding the 30% fat threshold recommended by the Chinese dietary guidelines (Table B8 in the Appendix).

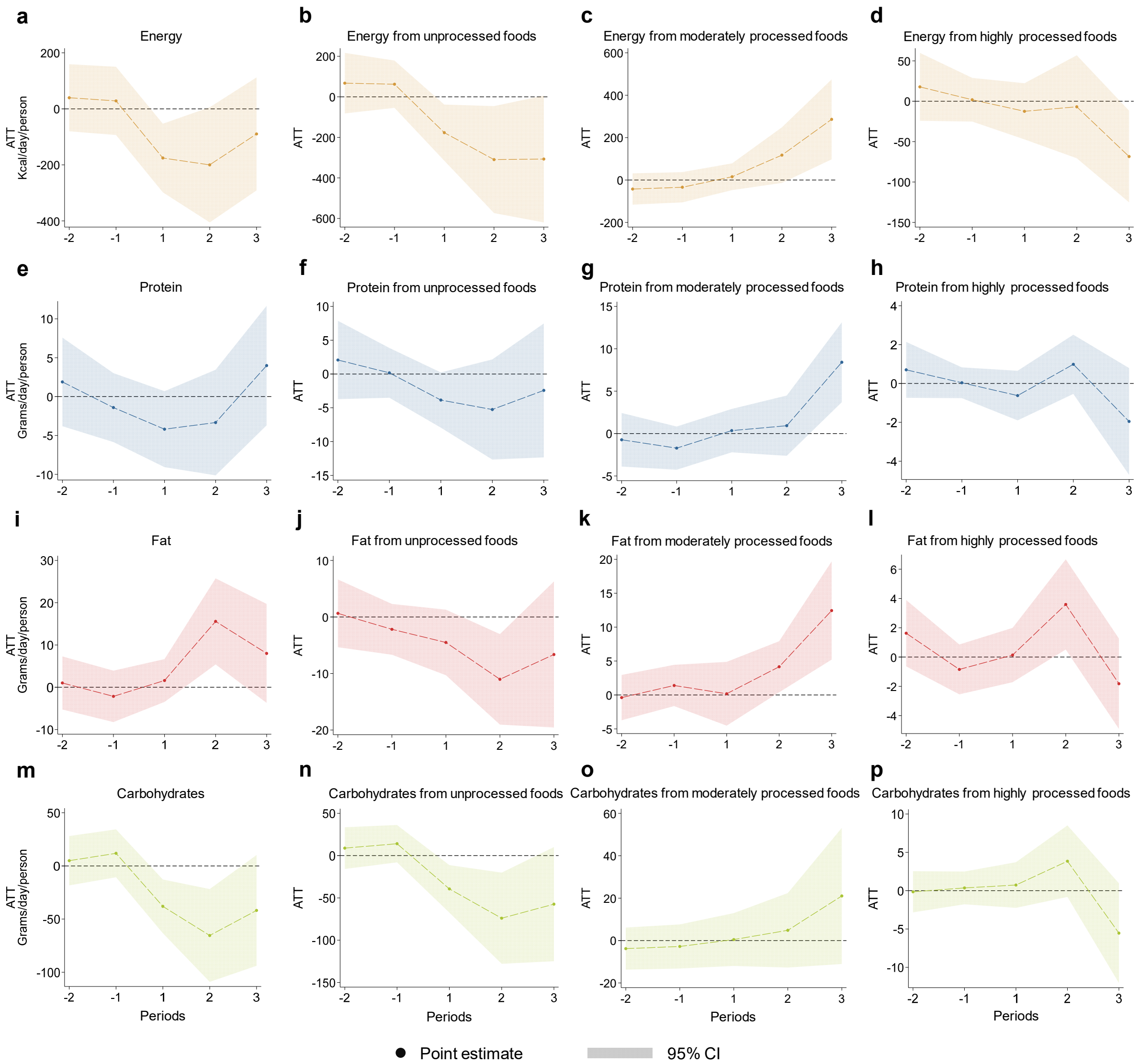


Fig. 3.4 Impacts of supermarkets on individual energy and macronutrient intake in total and from foods of different processing levels in China

Notes: **a,e,I,m**, Impacts on total energy, protein, fat, and carbohydrate intake, respectively. **b,f,j,n**, Impacts on intakes from unprocessed foods. **c,g,k,o**, Impacts on intakes from moderately processed foods. **d,h,l,p**, Impacts on intakes from highly processed foods. Average treatment effects on the treated (ATTs) estimated with DID regression models. The regression sample includes women studied for shopping and cooking time, as well as all adult household members (*n*=10,808). Coefficients can be interpreted in kcal or grams, as specified in the left-hand-side panels. Shaded areas represent 95% CIs, computed using standard errors clustered at the community-sex level. Each panel shows the effects for two periods before and three periods after supermarket entry.

Next, we assess the effects of supermarkets on dietary diversity, dietary balance, and dietary nutrient density (Fig. 3.5a,b,c). Supermarkets have no significant effect on dietary diversity for the full sample and most population subgroups. Interestingly, however, we see a significantly positive effect for individuals with below-average DDS, suggesting that supermarkets help to increase dietary diversity (Fig. 3.5a). Effects on dietary balance are statistically insignificant for all subgroups (Fig. 3.5b), indicating that supermarkets neither improve nor worsen people's adherence to the Chinese dietary guidelines.

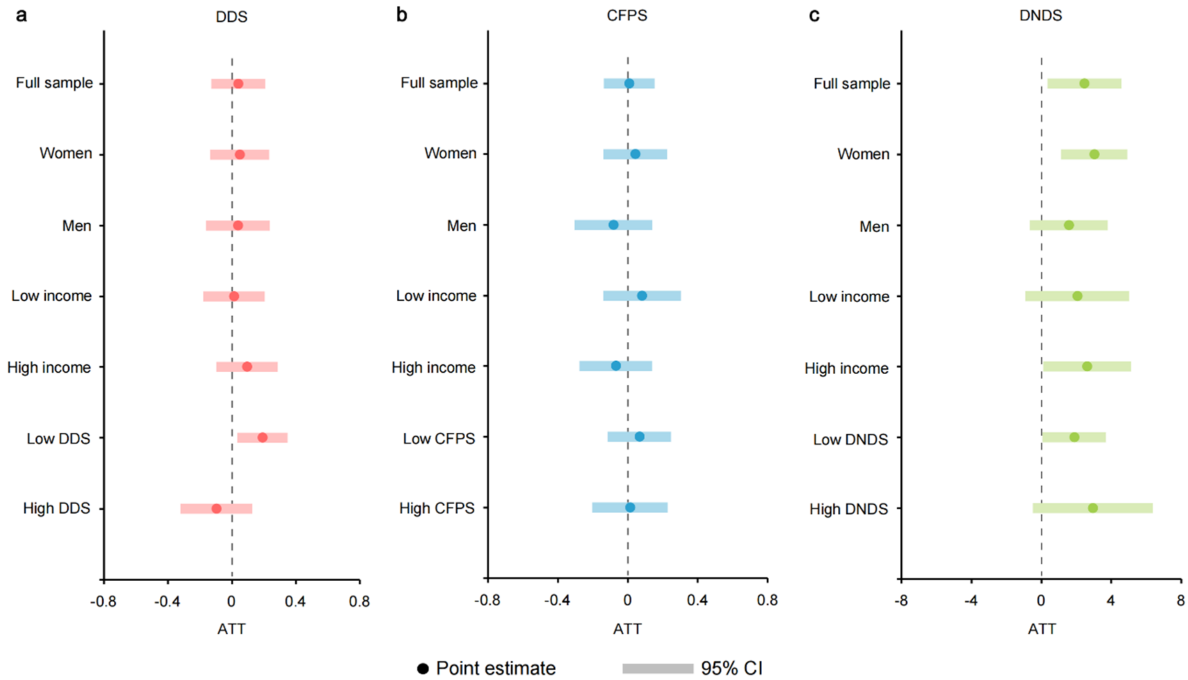


Fig. 3.5 Impacts of supermarkets on individual dietary quality in China

Notes: **a**, Impacts on dietary diversity, measured with the Dietary Diversity Score (DDS). **b**, Impacts on dietary balance, measured with the Chinese Food Pagoda Score (CFPS). **c**, Impacts on dietary nutrient density, measured with the Dietary Nutrient Density Score (DNDS). Average treatment effects on the treated (ATTs) estimated with DID regression models. The regression sample includes women studied for shopping and cooking time, as well as all adult household members (*n*=10,808). Shaded areas represent 95% CIs, computed using standard errors clustered at the community-sex level.

A more detailed analysis of food group alignment with recommended quantities and the role of supermarkets in this connection is shown in Figs. B3 and B4 in the Appendix. While supermarkets change dietary composition, for most food groups the effects are statistically insignificant. However, supermarkets significantly reduce the consumption of staple foods. Given that staple foods are overconsumed on average, this effect leads to closer alignment with dietary guidelines. Moreover, supermarkets seem to increase the consumption of salt and edible oil, leading to deviations from dietary guidelines. These results are consistent with the lower carbohydrate and higher fat intakes shown above.

Interestingly, supermarkets have a significantly positive effect on dietary nutrient density (Fig. 3.5c), suggesting that they help mitigate micronutrient deficiencies. These effects are particularly strong for women and individuals with below-average dietary nutrient density.

We also assess effects of supermarkets on nutritional outcomes, measured in terms of anthropometric indicators with a particular focus on obesity and the risk of diet-related non-communicable diseases. We find no significant impacts on the body mass index (BMI) or the likelihood of overweight and obesity, neither for the full sample nor for any of the subgroups (Table B9 in the Appendix).

3.4.5 Reallocation of saved time

We have shown that supermarkets reduce women's time spent on food shopping and cooking (on average, 23 minutes per day), so one interesting question is how women reallocate this saved time, or – in other words – how supermarkets affect women's engagement in other paid and unpaid activities. Results are shown in Table B10 in the Appendix. For women below 55 years of age, which is the official female retirement age in China, supermarkets increase the likelihood of participating in paid work by 17 percentage points, which is a sizeable effect. Note that these are not necessarily full-time jobs but also include part-time paid work and self-employment. For women already engaged in paid work, working hours do not seem to further increase. Nor do we find a significant effect on women's time spent on housework other than food shopping and cooking. However, supermarkets increase women's leisure time by about 19% (Table B10).

3.5 Discussion and conclusion

Supermarkets and other modern retailers have transformed people's food choices and daily routines. Earlier studies on the supermarket expansion in high-income countries since the 1960s often argued that there is a demand-driven relationship between supermarkets and women's shopping and cooking time, meaning that supermarkets were partly seen as response to increasing female employment and rising demand for time-saving food options (Abbott, 1963; Reardon et al., 2003). While plausible to some extent, such a demand-driven relationship has not been shown empirically due to the lack of suitable data. More recently, however, supermarkets have become more proactive in influencing lifestyles by reshaping food supplies (Ellickson, 2016). Many supermarkets have invested heavily in sourcing and distributing both processed and fresh foods, as seen in the USA in the 1990s, in China and Mexico in the 2000s, and in India in the 2010s (Lu & Reardon, 2018). Trade liberalization and economies of scale have further allowed supermarkets to expand into poorer regions, offering certain foods at lower prices than traditional markets (Minten et al., 2010; Rischke et al., 2015). Increased affordability makes supermarkets a viable option for broader populations, regardless of income or the opportunity cost of meal preparation time.

In this study, we have quantitatively evaluated the time-saving effects of supermarkets on women's unpaid work, using longitudinal data from China covering a time period of rapid supermarket expansion. We find that supermarkets have significantly reduced the time women spend on food shopping and cooking. Moreover, as the nature of supermarkets and their food offers evolved, these time-saving effects have increased over time. Less time needed for shopping and cooking can be explained by a broad range of foods found under one roof and consumers switching from unprocessed to moderately processed products. Other factors, such as changes in transport technologies and modern kitchen appliances, may also contribute to women's time savings, but we have controlled for such factors, so our estimates can be interpreted as net supermarket effects.

We expect that similar time-saving effects of supermarkets for women also occurred in high-income countries several decades ago, especially when modern supermarkets started to spread there in the 1960s and 1970s. And it is likely that these effects also occur in other LMICs, especially where meal preparation is additionally associated with time-consuming tasks such as fetching water and firewood, which are mostly performed by women. In such situations, the time-saving effects may even be larger than those observed in China.

Another contribution of our study is that we have addressed the concern that less shopping and cooking time through supermarkets could lower dietary quality and lead to negative nutritional outcomes. While we have shown that supermarkets increase the consumption of processed foods, this shift primarily involves moderately processed and not highly processed foods. Supermarkets also sell highly processed foods, which are increasingly consumed in

China, but highly processed foods are also available from traditional outlets, and the effects of supermarkets were found to be insignificant. Moderately processed foods, for which we found a significant supermarket effect, are not necessarily unhealthy. These foods retain many of the inherent properties and nutrients of the fresh, unprocessed foods, while reducing the time-consuming tasks associated with raw food preparation.

Our analysis reveals no significant negative effects of supermarkets on most indicators of dietary quality. In fact, we even observe some positive effects on diets, such as increased dietary diversity among individuals with below-average DDS, and enhanced dietary nutrient density among women and those with below-average dietary nutrient density. While fat intake increases through supermarkets, staple food and carbohydrate intakes decrease, resulting in lower total energy intakes, especially among those consuming above recommended levels. We did not find significant effects of supermarkets on body weight or overweight and obesity rates. Overall, despite certain dietary risks, supermarkets do not seem to be major drivers of dietary deteriorations in the Chinese context. However, the diet and nutrition effects of supermarkets depend on the particular context (Debela et al., 2020; Demmler et al., 2018; Liu et al., 2024; Otterbach et al., 2021; Zeng et al., 2019).

We also contribute to the literature on whether alleviating unpaid work can increase female labor supply. Previous studies found mixed results both in high-income countries and LMICs (Dinkelman & Ngai, 2022), probably because women's time allocation depends on context-specific factors, such as cultural norms, the relative productivity of paid versus unpaid work, and the availability of childcare options. Our results from China show that supermarkets have led to an increase in female labor force participation and leisure time, suggesting that reducing women's unpaid work burden can be an effective avenue towards female economic and social empowerment.

Our concrete results relate to China, but the general insights have implications for other countries as well. Worldwide, women disproportionately bear the burden of unpaid housework, contributing to and perpetuating female disempowerment (Fig. 3.6). Gender gaps are mostly due to deeply rooted social norms, which can be changed, but only through long societal processes. Hence, any innovations that ease women's unpaid work can help. Our study demonstrates the potential of supermarkets in this respect.

In Islamic regions, for example, social norms often assign women the responsibility of household labor while discouraging their participation in the labor market. Alleviating the housework burden through supermarkets may increase women's involvement in productive activities, such as household agricultural production, or at least benefit their psychological well-being through more leisure time. In East and Southeast Asia, as well as many parts of sub-Saharan Africa, social norms encourage both men and women to work for pay but often discourage men from sharing household chores. In such environments, focusing solely on creating new employment opportunities for women may not always lead to a more equitable distribution of unpaid work but increase women's time burden (Melaku et al., 2024). Integrated strategies that mitigate the unpaid labor burden while enhancing employment opportunities can empower women more sustainably.

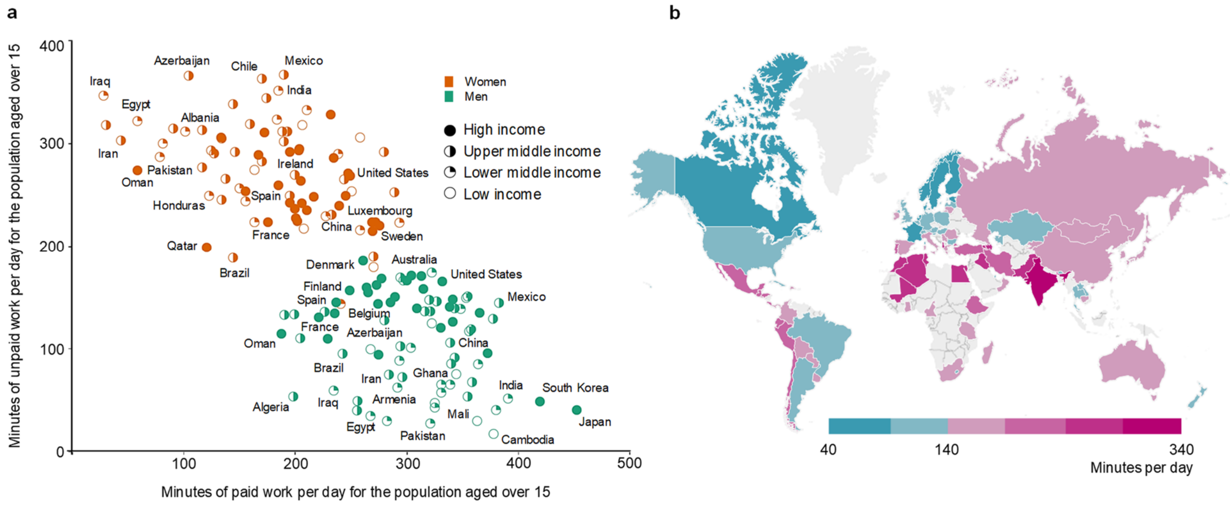


Fig. 3.6 Women's contribution to unpaid work worldwide

Notes: **a**, Women's and men's time (in minutes) spent on paid and unpaid work in 81 countries. **b**, Time (in minutes) per day that women spend more than men on unpaid work in 81 countries. Data are from the Organization for Economic Cooperation and Development (OECD) database (available at https://stats.oecd.org/Index.aspx?DataSetCode=TIME_USE), the Economic Commission for Latin America and the Caribbean (ECLAC) database (available at https://statistics.cepal.org/portal/databank/index.html?lang=en&indicator_id=2503&area_id=), and the United Nations Minimum Set of Gender Indicators (available at https://gender-data-hub-2-undesa.hub.arcgis.com/pages/indicators). The underlying time-use surveys were conducted in different years across countries; we selected data from the most recent year available for each country.

CHAPTER 4

Supermarket Expansion and Grain Farmers in China: Implications for Income and Resource Allocation

Abstract

The rapid expansion of supermarkets is modernizing grain value chains in developing countries; however, its implications for grain farmers remain underexplored. This study introduces a location-based framework and examines how supermarket expansion affects farmer income and resource allocation, using a panel of 5,221 grain farmers in China from 2006 to 2015. The results show no effects on grain income at the aggregate level, but significant variation across locations. Remote farmers earn higher grain income due to increased farm-gate prices, greater commercialization, and more resources allocated to grain production. In contrast, peri-urban farmers experience losses in grain income, but manage to compensate for these losses through shifting to off-farm work. Our findings highlight a spontaneous transformation among farmers driven by adaptive diversification strategies in response to supermarket expansion, offering insights for agricultural and retail policies in developing countries.

Keywords: supermarkets, grain farmer, income, resource allocation, China

4.1 Introduction

Efficient grain value chains are the backbone of food security, as grain products provide more than 50% of the world's dietary energy (Jones et al., 2020). However, in many developing countries, grain markets remain fragmented, offering limited sales opportunities and low farm-gate prices for producers while subjecting consumers to relatively high retail prices and occasional shortages (Burke et al., 2019). The expansion of supermarkets presents a potential solution by integrating value chains, coordinating with suppliers, standardizing quality, and optimizing logistics and distribution (Macchiavello et al., 2022; Reardon et al., 2003; Sexton & Xia, 2018). By streamlining operations, supermarkets can improve market efficiency and build more stable supply channels (Battersby & Watson, 2018; Gómez & Ricketts, 2013; Zhong et al., 2019).

Although supermarkets have dramatically reshaped grain value chains in many places, their impact on grain farmers' welfare is still under-researched (Barrett et al., 2022; Hamilton et al., 2020; Reardon et al., 2014). Grain production accounts for over 65% of global cultivated land, employs a substantial rural workforce, and contributes 20-40% of rural household incomes in developing Asia and sub-Saharan Africa (Bresciani et al., 2019; FAO, 2021). Yet, most existing studies focus on horticultural farmers (Miyata et al., 2009; Nuthalapati et al., 2020; Ogutu et al., 2020; Rao et al., 2012; Schwentesius & Gómez, 2002), likely because horticultural products are sold in ready-to-eat form, making farmers' transactions with supermarkets more direct and visible. In contrast, grains pass through multiple processors and intermediaries before reaching consumers. However, their non-perishable nature allows supermarkets to achieve economies of scale through extensive procurement networks, potentially resulting in an even greater impact on grain farmers compared to horticultural farmers. This study aims to address this knowledge gap by exploring how supermarket expansion influences grain farmers' incomes and their allocation of productive resources.

Supermarket expansion may bring both opportunities and challenges. Studies on horticultural farmers indicate that supermarkets can boost sales revenues by increasing demand, providing market information, and reducing transportation costs (Nuthalapati et al., 2020; Ogutu et al., 2020). These findings align with conventional wisdom that increasing market access improves producer income (Bergquist & Dinerstein, 2020; Burke et al., 2019; Negi et al., 2018), which may also apply to grain farmers. However, some other studies warn that supermarket-led vertical coordination with large processors and wholesalers may increase market concentration and shift bargaining power away from farmers (Barrett et al., 2022; Bignebat et al., 2009; Hamilton et al., 2020; Sexton & Xia, 2018). This concern is particularly relevant in Asia and sub-Saharan Africa, where smallholder farmers account for the majority of producers (Ma et al., 2022; Reardon et al., 2012; Vos & Cattaneo, 2021).

Another strand of literature further analyzes the heterogeneous effects of supermarkets. However, most such studies focus on unequal participation in supermarket procurement channels. They find that the benefits of supermarkets often accrue to farmers who meet certain asset and input thresholds (e.g., land, water, seeds, machinery, and credit), which enable them to comply with strict product standards and contract requirements (Hernandez et al., 2007; Neven et al., 2009; Ochieng & Ogutu, 2022). Supermarkets may even reduce prices and incomes for farmers who remain in traditional markets, particularly as supermarkets displace traditional retailers such as wet markets that may be the primary marketing channels for these farmers (Chang et al., 2015; Heijden & Vink, 2013). Some studies also suggest that farmers' ability to benefit from supermarkets depends on their access to external support from cooperatives, NGOs, or other agencies, which can assist in bargaining and meeting supermarket requirements (Bignebat et al., 2009; Liverpool-Tasie et al., 2020; Michelson, 2013; Miyata et al., 2009; Reardon et al., 2021).

Geographic heterogeneity in supermarket impacts has received little attention. Most existing research focuses on certain regions, such as vegetable farmers in Kiambu County, Kenya (Andersson et al., 2015; Neven et al., 2009; Ochieng & Ogutu, 2022; Ogutu et al., 2020; Rao et al., 2012); apple and green onion farmers in Shandong Province, China (Miyata et al., 2009); chili farmers in West Java, Indonesia (Chang et al., 2015); and vegetable farmers in Delhi and Haryana, India (Nuthalapati et al., 2020). These regions were already important production and supply centers for major consumer markets, such as big cities, even before supermarkets expanded, largely due to their proximity to these markets. Given the perishable nature of horticultural products, supermarkets likely prefer sourcing from these areas to minimize costs and achieve economies of scale rather than abusing market power, which finally benefits farmers. Hence, findings from these studies may not generalize to broader agricultural regions.

Unlike perishable horticultural products, grains can be stored and transported across regions, allowing supermarkets to establish integrated procurement and sales networks. Consequently, the impact of supermarket expansion on grain farmers may vary based on their geographic location and pre-existing market conditions. For example, in remote areas with limited sales channels, supermarket procurement networks may create new sales opportunities and increase farm-gate prices. Conversely, peri-urban farmers, who historically benefited from easier access to urban consumer markets and relatively higher prices, may experience greater competition and shifts in bargaining power as supermarkets consolidate supply chains. Understanding this heterogeneity is necessary for policymakers and modern retailers aiming to support farmers in adjusting to evolving grain value chains.

This study offers a location-based perspective on supermarket-driven market integration and its effects on grain farmers across regions using nationwide data from China. China provides a compelling case, with one of the world's largest grain-farming populations and a rapidly expanding supermarket sector. Specifically, I first introduce the modernization of grain value chains in China and the role of supermarkets. Next, I develop a conceptual framework that distinguishes urban, peri-urban, and remote grain markets to illustrate not only how supermarkets may impact farmers' income but also how farmers adjust the allocation of productive resources, including labor, land, and purchased inputs, in response to changing market conditions. The empirical analysis uses multiple data sources, including a longitudinal rural household survey and a geospatial database of supermarkets. The supermarket expansion is measured as the number of supermarket stores in rural areas at the county level, and econometric models are used to estimate heterogeneous effects across different farmer groups.

The remainder of this paper is structured as follows. Section 2 provides background on the modernization of grain value chains in China. Section 3 presents the conceptual framework and hypotheses. Section 4 details the data, variables, and empirical approach used in the analysis. Section 5 reports the results, and Section 6 discusses key findings and concludes.

4.2 Background on the modernization of grain value chains in China

The development of China's grain value chains has progressed through three major stages. In the first stage (1950s-1980s), the government implemented the Unified Procurement and Sales System, centralizing grain markets and restricting farmers' direct market participation (Lin, 1997). This state-controlled system limited competition and trade efficiency. The second stage, beginning in the mid-1980s, marked the liberalization of agricultural markets. The removal of price controls and trade restrictions provided farmers with greater market access. However, farm-gate prices and farmers' income remained low due to limited price transparency, widespread middlemen, and poor infrastructure. These challenges prevented farmers from fully benefiting from market reforms.

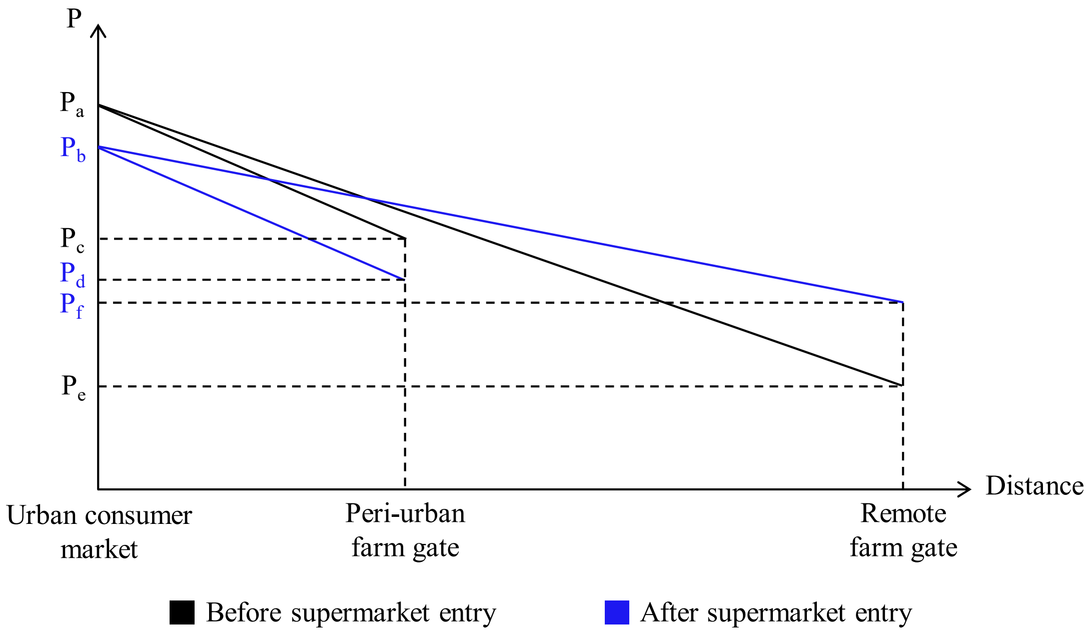
Since the late 1990s (the third stage), reforms have focused on creating more efficient market channels to connect farmers with consumers (Huang & Rozelle, 2006). Supermarkets emerged as key players in improving the efficiency of sourcing, logistics, storage, and retailing. To accelerate this transition, the government supported supermarket expansion through initiatives such as the "*Nonggaichao*" program, which promoted the conversion of traditional wet markets into supermarkets through acquisitions and mergers (Reardon et al., 2012), and the "*Nongchaoduijie*" program, which encouraged contract farming between supermarkets and farmers (Miyata et al., 2009). As a result, supermarkets have expanded in both urban and rural areas, reducing reliance on traditional intermediaries.

While the modernization of grain value chains is a global trend, China's transformation has been particularly rapid due to large-scale supermarket expansion. Unlike traditional value chains, where farmers' raw products pass through multiple intermediaries, modern chains emphasize direct transactions between suppliers and buyers, lowering transaction costs and improving efficiency. Supermarkets increasingly source directly from processors or specialized wholesale companies, while processors engage directly with farmers (Reardon et al., 2014). Although traditional value chains persist, their market share has diminished significantly as modern chains continue to expand.

4.3 Conceptual framework

This section provides a location-based framework to analyze the potentially heterogeneous effects of supermarket expansion on grain farmers. The framework considers three types of markets: urban, peri-urban, and remote markets. Urban markets mainly serve as consumer markets without grain production, while peri-urban and remote markets in rural areas both produce and consume grain but differ in proximity to urban areas. The midstream segment of value chains, including processors, wholesalers, and retailers, sources raw materials from rural areas, processes them, and distributes the products to urban consumers. A key assumption of this framework is the distance-attenuation effect: peri-urban farmers traditionally benefit from better market access and lower transaction costs, while remote farmers face structural disadvantages such as limited infrastructure, asymmetric market information, and high transportation costs, and thus high transaction costs.

Before the expansion of supermarkets, grain markets were fragmented. Due to multiple intermediaries, the urban retail price (P_a) was higher than the price received by farmers (Fig. 4.1). Transaction costs accounted for much of this price gap. Farmers in remote markets received an even lower price (P_e) compared to peri-urban farmers (P_c), primarily due to a longer supply chain and the involvement of more middlemen. This price disparity persisted even when product quality was the same across locations.



P_a, P_b: Urban consumer market price; P_c, P_d: Peri-urban farm-gate price; P_e, P_f: Remote farm-gate price;

Fig. 4.1 Urban retail and farm-gate grain prices before and after supermarket expansion

Commercialization rates also varied. Remote farmers had fewer buyers and lower market demand, leading to lower market participation. Although in China, government-supported agencies provided an alternative sales channel for unsold grain, their procurement prices were set below market levels to prevent price distortions, making this option less profitable. For example, government-procured grain accounted for only 5.7% of all grain sold by farmers in 2014 (Ministry of Agriculture of China, 2017). Therefore, remote farmers may retain more of their grain for household consumption, resulting in lower sales revenue relative to peri-urban farmers when producing the same quantity of grain.

Supermarket expansion directly reshapes price structures and market access for all farmers (Fig. 4.1). By coordinating with processors and wholesalers, supermarkets streamline supply chains, reducing intermediaries and transaction costs. For remote farmers, fewer middlemen, greater sales opportunities, and lower transaction costs allow them to capture a larger share of the final price, raising their farm-gate price from P_e to P_f, provided that supermarkets do not exercise excessive monopsony power. Higher farm-gate prices can also incentivize commercialization, encouraging subsistence farmers to sell a larger share of their harvest. Additionally, as supermarkets source more grain from remote areas, the urban retail price may decline from P_a to P_b due to increased overall supply.

In contrast, peri-urban farmers may experience a decline in their farm-gate price from P_c to P_d for two reasons. First, when supermarkets source more from remote areas, demand in nearby peri-urban markets falls. Second, given the lower grain prices in remote areas, supermarkets may source from remote markets and then sell in peri-urban markets, further depressing peri-urban farm-gate prices. Consequently, peri-urban farmers may face increased demand uncertainty and reduced commercialization rates. Equation (1) shows the key determinants of grain income, including farm-gate price, commercialization rate, and total grain production.

$$Grain\ income = P \times CR \times f(Land, Labor, Input) - Input \times \omega \tag{1}$$

where P and CR are the farm-gate price and the commercialization rate, respectively. Total production is a function of cultivated land area (Land), family labor input (Labor), and purchased inputs (Input). The term ω represents the price of purchased inputs. If the input use and total production remain unchanged, peri-urban farmers would have less grain revenue, while remote farmers' sales revenue would likely increase.

In fact, changes in price and commercialization would further influence grain income through altering the optimal allocation of household productive resources. Because China's rural households have transitioned from non-separability to greater separability, largely due to the liberalization of labor and land rental markets since the early 2000s (Bowlus & Sicular, 2003; Wu & Xin, 2012), I suppose a separable household model with well-functioning input markets. Farmers treat farm-gate prices as exogeneous and allocate resources to maximize profit. For remote farmers, higher farm-gate price increases the marginal revenue of grain production and then encourage greater input use until marginal costs align with the new price. For instance, they may expand cultivated land, intensify farming (e.g., planting an extra season or using higher-yield seed), or invest in fertilizers.

However, for peri-urban farmers, lower farm-gate prices increase the opportunity cost of grain farming, making alternative income sources, such as off-farm work or high-value agriculture, more attractive given their proximity to urban areas. In particular, supermarket expansion itself may stimulate off-farm labor markets, because establishing and running modern retail chains requires costly investments and create additional value in mid- and downstream segments of the value chains (Barrett et al., 2022; Reardon et al., 2014). A handful of recent studies have found evidence of job-creating effects from modernizing the retail sector (Lim & Kim, 2022; Zhang & Lei, 2015).

Notably, resource reallocation may interact dynamically with grain income changes, as farmers' production decisions may respond both prospectively to anticipated income changes and retrospectively to realized income changes. However, this study does not aim to establish causal relationships between income changes and resource adjustments. Instead, I focus on the net effects of supermarkets on grain farmers through the mechanisms shown in Fig. 4.2.

Based on this framework, the following analysis uses farm-level data from China to empirically examine (1) the potential heterogeneous effects of supermarkets on the grain income of peri-urban and remote farmers, (2) the mechanisms through which these effects materialize, including price changes, commercialization, and resource reallocation, and (3) the broader consequences of supermarket expansion for the total household income of grain farmers.

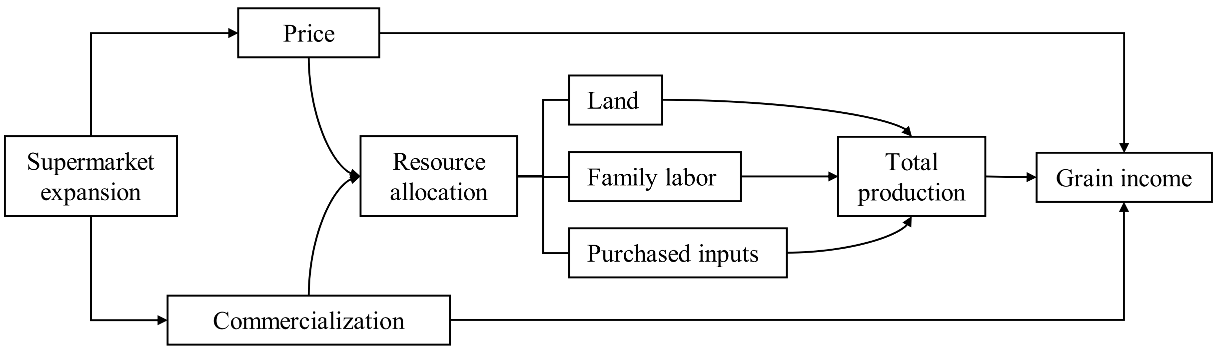


Fig. 4.2 Impact pathways of how supermarket expansion affects farmer's grain income

4.4 Data and methodology

4.4.1 Data source

This study utilizes several datasets to explore the impact of supermarkets on grain farmers in China. The supermarket dataset is derived from the Point of Interest (POI) database of Baidu Map, one of China's largest mapping and navigation service providers. This database contains detailed records of food retail stores since 2005, including store name, GPS coordinates, and classification (e.g., convenience store, grocery store, or supermarket). I use the ArcGIS tool to extract all supermarket locations from the POI data. To minimize classification errors, I manually verify store names to exclude entries that were misclassified as supermarkets (e.g., small convenience or grocery stores). Fig. 4.3 illustrates supermarket diffusion in China in 2005 and 2015.

Fig. 4.3 Diffusion of supermarkets in mainland China in 2005 and 2015

Notes: Each point represents a supermarket store. The number of supermarket stores is 31,568 in 2005 and 145,167 in 2015.

For farm-level data, I mainly use the China Health and Nutrition Survey (CHNS), a nationwide longitudinal survey conducted by the Chinese Center for Disease Control and Prevention and the University of North Carolina at Chapel Hill. CHNS collects economic, demographic, and social data from approximately 7,200 households and 30,000 individuals across 15 provinces and municipalities. Particularly, it includes aggregate production and sales data for grain crops (e.g., rice, wheat, and corn) produced by each household. Since the supermarket data is only available from 2005 onward, I only use data from the most recent four CHNS waves (2006, 2009, 2011, and 2015). The sample is restricted to rural households that produced grain products during the survey period. The total number of observations is 5,221, with 1,330 in 2006; 1,406 in 2009; 1,437 in 2011; and 1,048 in 2015.

However, CHNS does not record farm-gate prices for grains, a crucial variable for our analysis. I address this challenge in two ways. First, I use a proxy variable to perform the price analysis, which is detailed in the subsection 4.4.4. Second, I supplement our study with farm-level price data from the China Family Panel Studies (CFPS), a nationwide survey that tracks economic and social changes across around 16,000 households in China. I use the 2010 and 2011 CFPS waves, as they include farmers who produce and sell rice (paddy), wheat, or corn and provide detailed farm-gate price data for these grains. While the time span (two consecutive years) limits variations of variables over time and restricts panel analysis, pooling the data allows us to assess regional variations in supermarket expansion and grain sales. I focus on rural households that produced grains in the survey period and obtain a total of 5,230 observations. Notably, both the CHNS and CFPS samples vary significantly in geography, infrastructure, economic development, and urbanization levels, which enables us to examine the heterogeneous supermarket impacts on per-urban and remote farmers.

4.4.2 Measurement of supermarket expansion

This study defines supermarket expansion as the number of supermarket stores in rural areas within a given county and year. Focusing specifically on rural areas allows for a more accurate assessment of the extent of supermarket expansion. Consider two counties, A and B, with the same total number of supermarkets. In county A, supermarkets are concentrated in urban centers and primarily serve urban consumers. In contrast, county B has seen supermarkets expand into rural areas. Clearly, supermarkets in county B are more likely to influence farmers directly, as their physical presence in rural areas increases farmers' exposure to modern value chains.

A key challenge in measuring rural supermarket expansion is distinguishing rural supermarkets from urban ones, as our POI database does not explicitly provide this classification. To address this, I integrate multiple data sources. First, I obtain village coordinates from the National Database of Residential Points of China. I then match these coordinates with town-level administrative boundary data to determine the number of villages within each town. A town is classified as rural if it contains at least two villages. Figs. C1 and C2 illustrate this classification process. In the CHNS sample, the average number of supermarkets in rural areas of the sampled county increased from about 1 in 2006 to about 30 in 2015.

4.4.3 Measurement of peri-urban and remote farmers

This study does not use a dummy variable to classify peri-urban and remote farmers because there is no universal distance threshold applicable across different regions. Geographic features influence what a given distance means in practice. For example, in flat plains, farmers living 50 km from an urban center may still be considered peri-urban, whereas in hilly areas, even a 30 km distance may indicate remoteness due to difficult terrain and limited accessibility. Given this variability, using a fixed cutoff would be misleading. Instead, I generate a continuous index to measure farmers' proximity to urban consumer markets in order to capture the nuanced location-based heterogeneous effects of supermarkets.

For each surveyed community (neighborhood or village), CHNS provides an urbanicity index (UI) to measure its progress toward urbanization. The UI aggregates multiple indicators (e.g., population density, wages, transport access, infrastructure, and public services; see (Jones-Smith & Popkin, 2010) for technical details) and ranges from 0 to 100, with a higher UI indicating a higher level of urbanization. To reduce collinearity between urbanization and supermarket expansion, I compute a relative urbanicity index (RUI) to capture a community's urbanicity relative to other communities within the same province, rather than using the absolute UI value. First, I calculate the provincial average urbanicity index (PAI) by averaging the community-level UIs within each province. Next, I determine each community's deviation from that average: $D = UI - PAI$. Finally, I rescale this difference as $RUI = (D + 50)/100$, ensuring that RUI falls between 0 and 1. A community with a higher RUI can be considered more urban (i.e., closer to urban centers). In our rural household sample from CHNS, RUI ranges from 0 up to about 0.7.

For the CFPS sample, where a community-level urbanicity index is not available, I compute a county-level RUI as an alternative. The county-level UI is defined as the percentage of the urban population within the county, which is derived from the county-level statistical yearbook, and I calculate the CFPS RUI using the same method described above. Farmers in villages with higher RUI are closer to urban markets and are referred to as peri-urban farmers, while farmers in villages with lower RUI are referred to as remote farmers.

4.4.4 Measurement of dependent variables

I measure household income from grain production using three variables: grain production value, sales revenue from grain, and profit from grain. Sales revenue means the income from selling grains. Grain production value is the total market value of the harvest, equaling to the sales revenue plus the market value of any grain retained for household consumption. Profit is defined as the total production value minus the cost of purchased inputs. Purchased inputs include rented land, hired labor, chemical inputs (fertilizers, pesticides), seeds, and farm implements.

The direct mechanisms through which supermarkets affect farmers' grain income are the farm-gate price and the commercialization rate. Because the CHNS does not collect product-specific price data, I use production value per unit of land (Yuan per mu, 1 mu = 1/15 hectare) as a proxy for the farm-gate grain price. Production value per unit area can be decomposed into two components, i.e., land productivity and price. By controlling for factors that strongly influence land productivity in our regressions, I aim to isolate the price component of this metric. In other words, holding productivity constant, changes in production value per mu can be interpreted as changes in the farm-gate price. In addition, I perform robustness checks by using the CFPS data, which include actual farm-gate prices, to directly examine the effect of supermarket expansion on grain prices. The commercialization rate is defined as the percentage of total grain production that is sold, ranging from 0 to 100.

This study also considers indirect impact mechanisms, specifically how supermarket expansion influences the allocation of household resources to grain production. In particular, I examine three aspects of resource use: land use, which is the total area cultivated for grain; family labor use, which is the total hours household members spend on grain production in the given year; and purchased inputs, which refers to the expenditures on inputs for grain production, including costs of renting land, hiring labor, and purchasing seeds, chemical inputs, and farm implements.

4.4.5 Descriptive statistics

Table 4.1 shows the means and standard deviations for the main variables in our CHNS sample. I also include control variables such as household characteristics and regional heterogeneity. Household characteristics cover the household head's age, education, gender, and marital status, as well as household demographics including size and the number of children and elderly members. Regional heterogeneity is represented by non-agricultural gross domestic product (GDP) and population at the prefecture level, obtained from the China City Statistical Yearbook. All income and cost figures are converted to 2020 Yuan using the provincial consumer price index (CPI) from the National Bureau of Statistics of China.

Table 4.1 Summary statistics

Variables	Full sample (1)	Low RUI (2)	High RUI (3)
Panel A: Explanatory and explained variables			
Number of supermarkets in rural areas	25.52	23.23	27.88
	(57.10)	(43.14)	(68.53)
Sales revenue (2020 Yuan, thousands)	8.77	10.26	7.24
	(17.16)	(18.87)	(15.04)
Production value (2020 Yuan, thousands)	10.92	12.61	9.18
	(17.38)	(19.12)	(15.19)
Profit (2020 Yuan, thousands)	8.63	9.84	7.37
	(14.49)	(14.97)	(13.88)
Production value per mu (2020 Yuan, thousands)	1.95	1.97	1.94
	(1.59)	(1.61)	(1.56)
Commercialization rate (%)	63.64	64.53	62.73
	(32.06)	(32.05)	(32.05)
Cultivated land area (mu)	7.47	8.19	6.73
	(13.22)	(13.83)	(12.53)
Household hours spent on grain production	641.55	700.89	580.18
	(777.05)	(849.91)	(688.49)
Purchased inputs (2020 Yuan, thousands)	2.3	2.78	1.81
	(5.10)	(6.14)	(3.67)
Panel B: Household and regional characteristics			
Household head age	54.06	54.58	53.53
	(11.37)	(11.34)	(11.38)
Marital status (married = 1, other = 0)	0.82	0.82	0.82
	(0.38)	(0.38)	(0.39)
Household head education (years)	6.67	6.48	6.87
	(3.39)	(3.39)	(3.39)
Household size	3.73	3.8	3.67
	(1.65)	(1.70)	(1.59)
Number of children (under 18) in household	0.53	0.56	0.51
	(0.79)	(0.81)	(0.76)
Number of elderly (65 and over) in household	0.52	0.54	0.50
	(0.77)	(0.78)	(0.77)
Non-agricultural GDP (2020 Yuan, billions)	221.82	262.9	179.35
	(294.44)	(364.90)	(187.47)
Population (millions)	5.61	6.31	4.89
	(5.06)	(6.49)	(2.74)
Number of observations	5,221	2,654	2,567

Notes: Mean values are shown with standard deviations in parentheses. 1 mu = 1/15 of a hectare. The squared age of the household head, not shown in the table, is also included as a control variable.

Columns (2) and (3) of Table 4.1 compare key variables between farmers in low-RUI and high-RUI villages, using the median RUI as the threshold to split the sample. Compared to peri-urban farmers, remote farmers live in areas with fewer supermarkets, but they have higher grain sales revenue, production value, and profit. They also exhibit higher production value per mu, higher commercialization rates, and greater input intensity (land, labor, and purchased inputs) than peri-urban farmers.

Fig. 4.4 illustrates the relationship between supermarket expansion and grain production value in the raw CHNS data, controlling for household fixed effects. I observe a positive trend for remote farmers but a negative trend for peri-urban farmers. This implies heterogeneous effects of supermarkets on farmers, aligning with our conceptual framework. However, these patterns should not be interpreted as causal due to potential confounding factors. The next section addresses this issue using regression models.

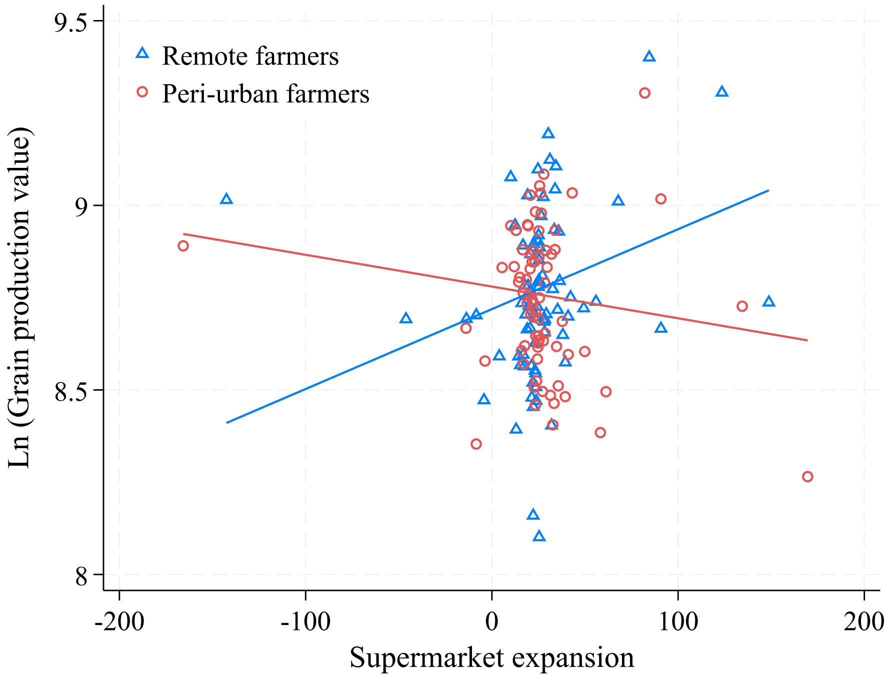


Fig. 4.4 Binned scatterplot between supermarket expansion and grain production value

Note: Household fixed effects is used.

4.4.6 Regression model

To explore the effects of supermarket expansion on grain farmers, I estimate the following household regression model:

$$Y_{ijkt} = \beta_0 + \beta_1 Supermarkets_{kt} + \beta_2 (Supermarkets_{kt} \times RUI_{jt}) + \gamma X + \mu_i + \lambda_t + \partial_t + \epsilon_{ijkt} \quad (2)$$

where Y_{ijkt} denotes the dependent variables, such as grain income, for household i in village j, county k, at year t. $Supermarkets_{kt}$ represents supermarket expansion, measured by the number of supermarket stores in rural areas of county k in year t. The interaction term $Supermarkets_{kt} \times RUI_{jt}$ captures how the effect of supermarket expansion varies with the relative urbanicity level of village j in year t. I focus on the coefficients β_1 and β_2, which indicate the direct effect of supermarket expansion on farmers and how this effect differs in different locations. If β_1 and β_2 have the same sign, the impact of supermarket expansion strengthens as RUI increases. Conversely, if their signs differ, supermarket expansion has a weaker, or even reversed, effect on farmers in more urbanized locations (higher RUI).

The potential endogeneity of $Supermarkets_{kt}$ and its interaction RUI_{ijt} may bias our estimates. I address this through refined model specifications. First, I add control variables (X) that are potentially correlated with supermarket expansion and farmers' production. The first set of controls includes household and regional characteristics listed in Table 4.1. Household characteristics account for human capital and productive resources, while regional economic and demographic factors influence both supermarket entry and local grain demand. The second set of controls includes RUI_{jt} to capture the direct effect of a village's urbanicity on the outcome, along with interaction terms between RUI and the household and regional characteristics. These interaction terms allow the relationships between the controls and the outcome variables to vary across villages with different RUI levels.

Additionally, multiple fixed effects (FE) are used to control for unobserved confounders. I include household FE (μ_i) to control for household- and regional-level time-invariant heterogeneity, such as solar intensity, soil quality, topography, and water resources. I use year FE (λ_t) to control for common shocks to farmers, such as agricultural policies and global price volatility. I also include province-by-year FE (∂_t) to account for regional time-varying factors, such as new technology adoption, climate change, regional economic policies, and shifts in people's dietary habits. Standard errors (ϵ_{ijkt}) are clustered at the household level to account for intra-household correlation over time.

Another potential concern is reverse causality. For instance, supermarkets may be more likely to expand into areas with higher grain productivity and production, as these regions offer a more stable grain supply. However, local grain production is only a minor contributing factor of supermarket expansion, as supermarkets mainly rely on the sale of packed and processed foods rather than grain products for profits. Therefore, reverse causality is unlikely to significantly bias our estimates.

4.5 Results

4.5.1 Effects of supermarkets on grain income

Table 4.2 shows the estimated effects of supermarket expansion on farmers' grain income indicators, including sales revenue, production value, and profit, based on our main regression model. I estimate these effects both without and with control variables, and the estimates are statistically significant and robust across all specifications. The results show significantly positive estimates for supermarket expansion and negative estimates for its interaction with the

Table 4.2 Impact of supermarket expansion on grain income

	Ln Sales revenue		Ln Production value		Ln Profit	
	(1)	(2)	(3)	(4)	(5)	(6)
Supermarkets	0.0047***	0.0080***	0.0043***	0.0055***	0.0064***	0.0080***
	(0.0017)	(0.0019)	(0.0014)	(0.0016)	(0.0017)	(0.0019)
Supermarkets×RUI	-0.0115***	-0.0214***	-0.0097***	-0.0133***	-0.0143***	-0.0186***
	(0.0038)	(0.0047)	(0.0031)	(0.0038)	(0.0043)	(0.0048)
Controls	No	Yes	No	Yes	No	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,515	4,515	5,221	5,221	5,192	5,192

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. Full model results and control variables are shown in Table C1 in the Appendix. ***$p < 0.01$.

relative urbanicity index, suggesting that the benefits of supermarket expansion to farmers' grain income decrease as RUI increases. In other words, the positive impact of supermarkets is larger for farmers in more remote areas and smaller (or negative) for those closer to urban centers. The turning point occurs at approximately RUI = 0.4. In our CHNS sample, about 70% of farmers have an RUI below 0.4, while 30% have an RUI above 0.4. This means that roughly 70% of grain-farming households (those relatively far from urban consumer markets) experience grain income growth due to supermarket expansion, whereas the remaining 30% of households (those relatively close to urban markets) experience a decline in grain income.

Fig. 4.5 illustrates the marginal effects of supermarket expansion across farmers with different RUI levels. For remote farmers (RUI < 0.4), supermarkets have a positive impact on grain income. For example, at RUI = 0.2, one additional supermarket entry increases sales revenue, production value, and profit by about 0.4%, 0.3%, and 0.4%, respectively. In contrast, for peri-urban farmers (RUI > 0.4), the effect turns negative, and the negative impact intensifies as RUI increases. For example, at RUI = 0.6, one additional supermarket decreases sales revenue, production value, and profit by about 0.5%, 0.2%, and 0.3%, respectively. Given that

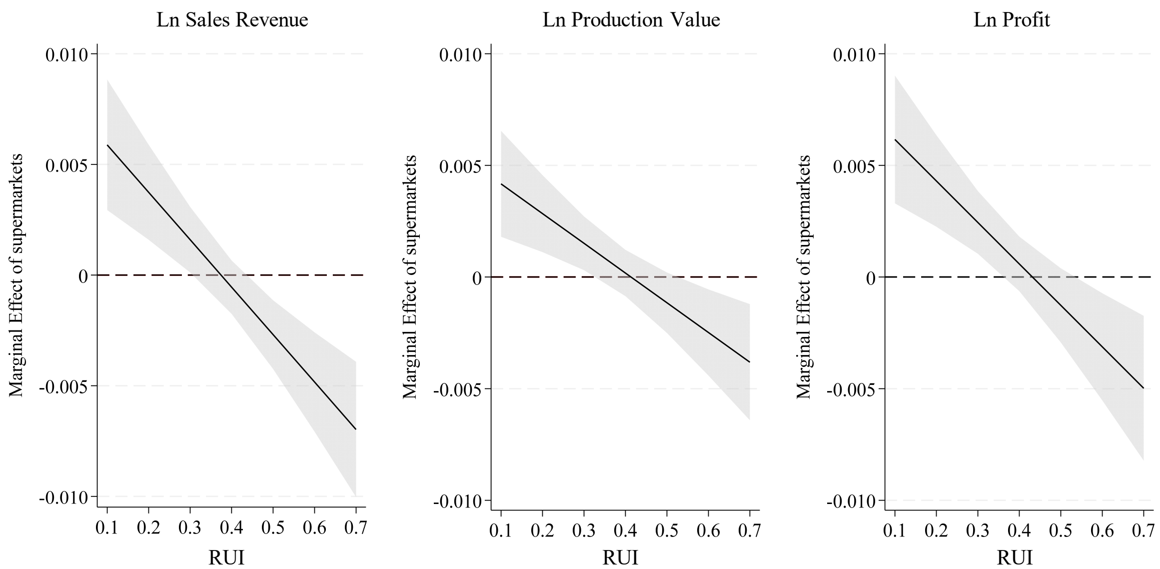


Fig. 4.5 Marginal effects of supermarkets on grain income by different RUI levels

Notes: The calculation of marginal effects is based on the regression results in columns (2), (4), and (6) of Table 4.2. The lines measure the estimated changes in grain incomes, and the shaded areas show the 95% confidence intervals.

the average number of supermarkets during our study period (2006-2015) is about 25 (column (1) of Table 1), the impact of supermarket expansion on farmers' income is economically significant in China. These results support the hypothesis from our conceptual framework that the location of farmers (relative remoteness versus urban proximity) shapes whether supermarkets help or hurt their grain income.

I also look at the impact of supermarkets on farmers' grain income without including the interaction term, as shown in Table C2 in the Appendix. The estimates are close to zero and statistically insignificant, suggesting that supermarkets do not have an overall positive or negative impact on all farmers as a group, except for heterogeneous impacts among peri-urban and remote farmers.

4.5.2 Effects of supermarkets on the farm-gate price and commercialization rate

This subsection examines the direct mechanisms (i.e., price and commercialization) through which supermarket expansion affects grain income. In the CHNS sample, production value per mu serves as a proxy for the farm-gate grain price. Household-level control variables, such as head's education and household size, and several fixed effects help account for productivity heterogeneity that could bias our estimates. Column (1) of Table 4.3 present the results for the farm-gate price proxy. Supermarket expansion has a positive effect on production value per mu, but this effect decreases as RUI increases, with a turning point around RUI = 0.4. This implies that supermarkets increase the farm-gate price for remote farmers while reducing it for peri-urban farmers, mirroring the heterogeneous effects observed for grain incomes in subsection 4.5.1.

I perform several robustness checks for the price effects. First, farm size is another potential confounding factor, as it may influence economies of scale, productivity, and then price (e.g., (Muyanga & Jayne, 2019; Sheng et al., 2019). I address this concern by controlling for household cultivated land area in a separate regression. The estimates, shown in column (2) of Table 4.3, remain largely unchanged. Second, to ensure our results are not driven by specific crops, I conduct subgroup analyses separately for farmers in rice-, wheat-, and corn-producing provinces. The estimates, presented in columns (1)-(3) of Table C4 in the Appendix, remain significant and consistent across all sub-groups. In addition, I restrict the sample to smallholder farmers, defined as those cultivating less than 2 hectares of land (Khalil et al., 2017), to rule out the influence of larger farms that might have different sales channels. This excludes 182 observations, yet the estimates, shown in column (4) of Table C4 in the Appendix, continue to support our findings.

Table 4.3 Impact of supermarket expansion on production value per unit land area

	Ln Production value per mu	
	(1)	(2)
Supermarkets	0.0031**	0.0037***
	(0.0012)	(0.0013)
Supermarkets×RUI	-0.0078**	-0.0094***
	(0.0030)	(0.0031)
Ln Land area	No	Yes
Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	5,221	5,221

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. Full model results and control variables are shown in Table C3 in the Appendix. ***$p < 0.01$, **$p < 0.05$.

Further, I directly estimate the impact of supermarkets on the farm-gate price using the CFPS sample. The regressions include the same control variables as in Equation (2) but employ different fixed effects. I use province FE and crop FE to account for regional and crop-specific heterogeneity, respectively, and include crop-by-year FE to control for crop-specific market volatility over time. Table 4.4 presents the model specifications and estimates, which align with the findings in Table 4.3. Specifically, supermarket expansion has a positive effect on farm-gate prices, but its interaction with RUI is negative, with a turning point at approximately RUI = 0.4. These results confirm our hypothesis that supermarkets lower prices for peri-urban farmers while increasing prices for remote farmers.

Next, Table 4.5 shows the effects of supermarkets on farmers' grain commercialization. In the baseline model (column (1)), which does not account for the interaction between supermarket expansion and commercialization rate, the overall effect of supermarket expansion is statistically insignificant. However, after including the interaction term (column (2)), the results show a significantly positive coefficient for supermarket expansion and a negative

Table 4.4 Impact of supermarket expansion on the farm-gate grain price using CFPS data

	Ln Farm-gate grain price			
	(1)	(2)	(3)	(4)
Supermarkets	0.0026***	0.0015*	0.0025***	0.0019**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Supermarkets×RUI	-0.0063***	-0.0037*	-0.0058***	-0.0045**
	(0.0023)	(0.0021)	(0.0022)	(0.0022)
Controls	Yes	Yes	Yes	Yes
Ln Land area	No	No	No	Yes
Province FE	Yes	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-by-year FE	No	Yes	No	No
Crop-by-year FE	No	No	Yes	Yes
N	5,230	5,230	5,230	5,230

Notes: Each column reports coefficients from a fixed-effects regression using the CFPS sample. Standard errors (in parentheses) are clustered at the household level. Control variables listed in equation (2) are also used here. Full model results and control variables are shown in Table C5 in the Appendix. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4.5 Impact of supermarket expansion on farmers' commercialization

	Commercialization rate		
	(1)	(2)	(3)
Supermarkets	0.0273	0.1772***	0.1497***
	(0.0170)	(0.0555)	(0.0551)
Supermarkets×RUI		-0.4311***	-0.3664***
		(0.1396)	(0.1375)
Ln Land area	No	No	Yes
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes
N	5,221	5,221	5,221

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. Full model results and control variables are shown in Table C6 in the Appendix. $^{***}p < 0.01$.

coefficient for the interaction term. To rule out the concern that our results are due to the changes in land area over time, I also control for household cultivated land area (column (3)), and the results are robust. These confirm that supermarket expansion encourages greater market participation (higher commercialization) among remote farmers, but has the opposite effect in more urbanized (peri-urban) regions.

Notably, the decline in commercialization rates among peri-urban farmers does not indicate a shift back to subsistence farming. In China, the average grain commercialization rate for both peri-urban and remote farmers already exceeds 60% (Table 4.1), a level higher than in many other developing countries (Do & Nguyen, 2024). Rather, this small decline for peri-urban areas reflects a reduced gap in market access between peri-urban and remote regions, leading to a new market equilibrium based on more efficient supply and demand chains supported by supermarkets. Moreover, the marginal effect of supermarket expansion on peri-urban farmers is modest. Even in villages very close to urban areas (e.g., RUI = 0.7), one additional supermarket lowers the commercialization rate by only 0.12 percentage points.

4.5.3 Effects of supermarkets on resource allocation

This subsection examines the indirect mechanisms (production inputs) through which supermarket expansion affects grain income. Table 4.6 presents the effects of supermarket expansion on three resource allocation outcomes: cultivated land area, household labor devoted to grain, and purchased input expenditures.

For household cultivated land area, the results in column (1) of Table 4.6 show a positive but decreasing impact of supermarkets, with a turning point at about RUI = 0.4. This finding supports our hypothesis that remote farmers tend to expand production due to higher farm-gate prices and commercialization, while peri-urban farmers reduce their land under grain cultivation. However, the marginal effects of supermarkets on land use are quite limited in magnitude. For example, for a remote farmer with RUI = 0.2, an additional supermarket increases cultivated land by only 0.08%, and for a peri-urban farmer with RUI = 0.6, it decreases cultivated land by only 0.07%.

Two key constraints likely explain this limited impact on land use. First, although China permitted farmland rental in 2002, the absence of land certificates during our study period kept the rental market small and mostly confined within villages. The widespread issuance of land certificates began after 2015, which is beyond the scope of our data. Second, most grain farmers in China are smallholders who face credit constraints that limit their ability to rent additional land.

Table 4.6 Impact of supermarket expansion on farmers' resource allocation

	Ln Land area	Ln Grain production hours	Ln Purchased input cost
	(1)	(2)	(3)
Supermarkets	0.0015**	0.0067***	0.0074***
	(0.0010)	(0.0019)	(0.0025)
Supermarkets×RUI	-0.0037**	-0.0127***	-0.0257***
	(0.0018)	(0.0047)	(0.0065)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes
N	5,221	5,221	5,221

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. Full model results and control variables are shown in Table C7. ***$p < 0.01$, **$p < 0.05$.

Columns (2) and (3) of Table 4.6 present the effects of supermarket expansion on household labor use (total hours spent by household members on grain production) and purchased inputs (cost of purchased inputs). Both labor and input use show positive but diminishing effects of supermarkets, yet with different turning points. For household labor, the expansion effect remains positive until about RUI < 0.5, a range that covers approximately 90% of our sample. In contrast, for purchased inputs, the supermarket effect turns from positive to negative around RUI = 0.3. Since only about 30% of our sample has an RUI below this threshold, only the most remote farmers increase their use of purchased inputs as supermarkets expand.

The higher turning point for household labor (0.5) relative to purchased inputs (0.3) suggests that as supermarkets improve market access, remote farmers increasingly rely on labor rather than capital inputs, such as chemical fertilizers and machinery, to expand production. This finding is consistent with recent studies on smallholder transformation (Blanco & Raurich, 2022; Mizik et al., 2025), which find that labor-intensive adjustments often prevail over capital-intensive investments among smallholder farmers.

4.5.4 Effects of supermarkets on other income sources and gross income

The heterogeneous effects of supermarket expansion on grain income among remote and peri-urban farmers may lead to spillover effects on other income sources. For remote farmers, an increase in grain income raises the opportunity cost of engaging in alternative income-generating activities, such as off-farm work and non-grain agricultural production. In contrast, for peri-urban farmers, lower grain income reduces this opportunity cost, possibly prompting a reallocation of household labor to other activities. However, it is still unclear which specific activities remote farmers might reduce to accommodate expanded grain production, and which activities peri-urban farmers might prioritize to compensate for grain income losses. To address this, this study examines the effects of supermarkets on farmers' participation in off-farm work and in non-grain agricultural production, as well as the income earned from these activities.

I first assess the effects on off-farm work. Participation in off-farm work is measured by a dummy variable indicating whether a household earns any off-farm income in a given year. The regression results in column (1) of Table 4.7 show that supermarket expansion slightly increases the likelihood of engaging in off-farm work, yet primarily for peri-urban farmers, as indicated by the interaction term. Column (2) of Table 4.7 further reveals a negative effect on off-farm income for farmers with low RUI (remote farmers), implying that remote farmers earn less off-farm income as supermarkets expand. This is likely because they allocate more labor to grain production, as shown in Table 4.6. In contrast, for farmers with high RUI (peri-urban farmers), supermarkets increase off-farm income, suggesting that off-farm work is an alternative income channel to offset grain income losses.

Columns (3) and (4) of Table 4.7 present the effects of supermarkets on non-grain agricultural production. Here, participation in non-grain agricultural production is defined as a dummy variable indicating whether a household engages in any horticultural production, livestock production, or fishing in the given year. The results show no significant effects on either participation in non-grain agricultural production or sales revenue of non-grain agricultural products, suggesting that grain farmers do not substantially reallocate resources to these alternative agricultural activities in response to supermarket expansion.

Finally, this study assesses the supermarket impact on farmers' gross household income from all sources except retirement pensions, as shown in Table C9 in the Appendix. I find a significant but small positive impact on gross income. An additional entry of supermarkets increases gross income by about 0.1%, and this impact does not differ between remote and peri-urban farmers. In other words, all farmers experience a slight overall income gain from the expansion of supermarkets. In particular, peri-urban farmers are able to fully offset their grain income losses through increased participation in off-farm work, leaving their total household income modestly improved.

Table 4.7 Impact of supermarkets on off-farm work and non-grain agricultural production

	Participation in off-farm work (dummy)	Ln Income from off-farm work
	(1)	(2)
Supermarkets	-0.0012	-0.0099^{**}
	(0.0009)	(0.0040)
Supermarkets×RUI	0.0035^{*}	0.0254^{***}
	(0.0020)	(0.0099)
Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	5,221	2,751
	Engaging in non-grain agricultural production (dummy)	Income from selling non-grain agricultural products
	(3)	(4)
Supermarkets	-0.0005	-0.0014
	(0.0005)	(0.0031)
Supermarkets×RUI	0.0007	-0.0014
	(0.0013)	(0.0081)
Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	5,221	1,842

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. Full model results and control variables are shown in Table C8 in the Appendix. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.6 Discussion and conclusion

The expansion of large modern retailers, particularly supermarkets, is reshaping food value chains in developing countries by streamlining operations and increasing efficiency. Yet, smallholder farmers continue to dominate the production sector in many places, making their adaptation to these changes a critical policy concern. Designing policies to support smallholder-based farming systems requires comprehensive, quantitative assessments of supermarket impacts. While prior studies offer valuable insights, most have focused on horticultural farmers in specific regions and emphasized asset-based heterogeneity. This study introduces a location-based framework to assess how supermarket expansion influences grain farmers in different regions, using farm-level data and supermarket distribution information from China.

Our empirical results reveal no significant overall effect of supermarket expansion on grain income at the aggregate level. However, analysis by geographic location shows stark heterogeneity: supermarkets reduce grain income for peri-urban farmers while increasing grain income for remote farmers. This heterogeneity arises from both price and commercialization effects. Remote farmers benefit from higher farm-gate prices and greater commercialization, likely due to enhanced market access and expanded sales channels. In contrast, peri-urban farmers face declining prices and reduced commercialization rates, potentially due to intensified competition and increased market supply from remote areas.

Beyond these direct mechanisms, I also examine indirect effects related to resource allocation. Remote farmers, incentivized by better market conditions, invest more land, labor, and purchased inputs (e.g., fertilizer and implements) into grain production. Conversely, peri-urban farmers gradually shift away from grain farming, reallocating labor to off-farm work to offset income losses. Despite the contrasting effects on grain income, supermarket expansion has a net positive impact on overall household income for both groups, suggesting that farmers adapt through income diversification strategies.

This study deepens the understanding of supermarket-farmer relations by offering a geographic perspective. Various strategies proposed over the past decade to enhance farmer participation in many developing countries (Vos & Cattaneo, 2021; Ørtenblad et al., 2023), but sustained integration into supermarket supply chains remains limited (Andersson et al., 2015; Miyata et al., 2009). The existing literature has not sufficiently addressed why many farmers are excluded. Our findings suggest that geographic location may partly explain this gap. For grain products, supermarkets sourcing from remote regions can reduce procurement costs and achieve economies of scale. However, for peri-urban farmers, supermarket expansion erodes their traditional advantage of proximity to urban consumer markets. Given that grain production is both land- and labor-intensive, the increased supply from remote areas raises competition and increases the opportunity cost of grain farming in peri-urban areas, making off-farm work or high-value agriculture more viable for those farmers.

Our findings also contribute to ongoing debates about supporting smallholder farms versus facilitating structural transformation. In regions like Asia, where average landholdings are small, policies often promote smallholder family farming to reduce poverty. However, focusing too heavily on the advantage of smallholder farming would neglect the relatively low allocative efficiency of resources in such systems (Ma et al., 2022). Smallholder farmers often rely on excessive family labor inputs to achieve higher land productivity and income, but the spread of modern production services, mechanization, and chemical inputs is gradually eroding this labor productivity premium. Our results indicate that supermarket expansion improves the allocative efficiency of land and labor: remote grain farmers expand production, while peri-urban grain farmers reallocate resources to more productive uses to optimize household income.

This study is also relevant to the emerging literature about market concentration and the potential market power of modern food retailers. Some studies highlight a declining farm share of the consumer food dollar (e.g., Kelly et al., 2015; Yi et al., 2021), raising the concern that supermarkets may abuse their market power to the detriment of farmers. However, our results show no significant effects of supermarkets on grain incomes in the full-sample regression, suggesting that supermarkets do not systematically extract surplus from farmers. Rather, the impacts vary by locations, with supermarkets improving grain incomes in remote areas and reducing them in peri-urban areas.

Finally, while I believe that our location-based framework has potential applications beyond China, I acknowledge limitations in external validity. China's grain self-sufficiency exceeds 90% (Liang et al., 2023), meaning that supermarkets primarily source and sell domestically produced grain. Countries that rely heavily on grain imports may experience different supermarket impacts, as supermarkets' procurement decisions could be more influenced by global market conditions than by domestic production. Additionally, the supermarket effects observed in China may be partly due to the well-developed infrastructure, such as roads, that enables supermarkets to establish regional procurement networks and benefit remote farmers. In settings with poorer infrastructure, such positive effects might be less pronounced or slower to materialize. Therefore, to build mutually beneficial relationships between supermarkets and farmers, policy efforts should not only regulate supermarket behavior but also invest in rural public goods such as roads and logistics systems.

CHAPTER 5

General Conclusion

5.1 Main findings

This dissertation demonstrates that the expansion of supermarkets in LMICs represents a systemic transformation of agri-food systems. Not only do supermarkets provide new places to shop, but they have also become dominant nodes in agri-food value chains, reshaping how food is produced, traded, and consumed. The rapid "supermarket revolution" underway in countries such as China thus has far-reaching implications for both consumers and producers (Barrett et al., 2022; Qaim, 2017; Yuan et al., 2021). This dissertation includes three empirical chapters that analyze whether this retail transformation is inclusive or, more specifically, whether it creates new opportunities to address long-standing challenges faced by vulnerable groups in agri-food systems, namely children, women, and smallholder farmers.

A consistent message throughout these chapters is that supermarkets provide tangible benefits to disadvantaged subpopulations. Supermarkets in China have improved nutrition for children, reduced unpaid time burdens for women, and increased market opportunities for smallholder farmers. These benefits are especially pronounced among marginalized populations, including children from rural and low-income households, women who spend considerable time shopping for and cooking food, and remote farmers, by integrating them into more modern and efficient food markets.

In particular, widely discussed concerns, such as the excessive consumption of highly processed foods that degrade diets or powerful retailers squeezing out smallholders, did not materialize in any significant way in the China context analyzed. On the contrary, the evidence presented in this dissertation suggests that supermarkets, as part of a transforming agri-food system, can contribute to achieving several SDGs through mitigating persistent development problems such as child malnutrition, women's disempowerment, and rural poverty. Supermarket expansion, therefore, represents not merely a retail trend, but a useful tool for improving the well-being of society.

5.2 Limitations and scope for future research

While the findings presented in this dissertation are encouraging, it is important to acknowledge its limitations and identify areas that warrant further study.

First, the empirical analyses do not capture the long-term health effects of supermarket expansion very well. Although the CHNS covers around ten years, most individuals and households in the sample were exposed to supermarkets for only about two to three years. While the regression results show limited health risks, slow-moving, cumulative outcomes resulting from sustained dietary changes remain possible but have not been studied in China and other LMICs. For instance, diets that include more packaged and processed foods could contribute to health issues such as diabetes or cardiovascular disease over a decade or more even if the short-term impacts are modest. Another concern is the substitution of meat for vegetables (Fig. B4), partly because supermarkets tend to reduce meat prices (Table 2.6). Although both average meat and vegetable consumption among Chinese populations remained within recommended ranges during the study period, their trends toward outside the recommendations are noteworthy (Fig. B4). Future research should therefore extend the observation window and consider tracking cohorts over time to assess the cumulative effects of supermarket-driven dietary changes.

Second, the mechanisms through which supermarkets affect smallholder incomes need deeper investigation. Chapter 4 provides evidence of increased commercialization and farm income among remote grain farmers, but the exact channels deserve closer exploration. We inferred that improved sales opportunities and higher farm-gate prices were key drivers of income gains. However, research gaps remain about how, in practice, farmers negotiate with supermarkets or their agents and adjust their production decisions. Do farmers form cooperatives to meet volume and quality requirements? What role do local governments play in linking farmers, processors, and supermarkets? And how do traditional intermediaries respond to the rise of direct procurement by supermarkets? These questions can only be addressed through a mix of quantitative and qualitative research, such as interviews with farmers and supermarket procurement managers. A better understanding of these mechanisms would not only enrich the literature but also inform policy interventions to support the welfare of both supermarkets and smallholder farmers.

Third, more attention should be given to the changing agri-food systems in the post-supermarketization era. The CHNS data used in this dissertation largely cover the 2000s and mid-2010s. Yet, the food retail landscape in China has continued to evolve dramatically since then. One major feature is the rise of e-commerce and online-to-offline integration (Lu & Reardon, 2018). Both urban and rural consumers increasingly buy foods via mobile apps, and supermarkets are also experimenting with digital platforms. These developments may enhance or reverse the impacts observed in this dissertation. For instance, e-commerce and efficient delivery services may further improve the access of both healthy and unhealth foods in remote areas.

Moreover, the supermarket sector itself is undergoing "de-middleization" in China. Conventional supermarkets such as Walmart and RT-Mart (comparable to Lidl and Penny in Germany) have recently seen declines in both the store numbers and sales, while two contrasting formats – super discounters such as Pinduoduo and premium (or club) supermarkets such as Freshippo, Sam's Club, and Pangdonglai (comparable to Edeka and Rewe in Germany) – are expanding rapidly.[8] This bifurcation may be related to changing consumer preferences, growing income inequality, social media-based marketing, and so on. Future research should evaluate how these new forms of retail affect dietary outcomes and the welfare of smallholder farmers in the 2020s, which is essential to support policymaking in the next stage of retail modernization.

Finally, while the findings of this dissertation offer important insights, they are grounded in the specific context of China, and their external validity is a potential concern. Supermarkets are profit-driven enterprises, and the favorable outcomes observed in our studies largely reflect the spillover effects rather than deliberate inclusion strategies. Differences in dietary habits, social norms, infrastructure, income levels, policy environments, and other observed and unobserved conditions may lead to separate business models of supermarkets and, consequently, distinct impacts on nutrition, gender equity, and smallholder livelihoods. A thorough understanding of the role of supermarkets requires more studies based on diverse settings.

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[8] For example, between 2020 and 2024, the number of Walmart stores in China declined from 412 to about 300, while its sub-brand, Sam's Club, expanded from 29 to 48 stores. Over the same period, Walmart's total sales in China (including Sam's Club) grew from 10.7 billion USD to 17.0 billion USD, with Sam's Club accounting for about 70%. Source: https://www.jiemian.com/article/11679094.html and https://36kr.com/p/3191874033246849.

5.3 Policy recommendations

The specific policy implications of our empirical studies have been described in the preceding chapters. This section puts forward overarching principles for future sustainable development policies, applicable not only to the retail sector but to broader agri-food systems, and relevant not only to China but also to other LMICs.

First, systemic challenges demand systemic solutions. As noted in Chapter 1, interrelated issues such as child malnutrition, women's disempowerment, and smallholder poverty are not only due to economic underdevelopment but also rooted in entrenched social norms. Isolated interventions likely risk unintended trade-offs. For instance, nutrition education targeted at women may improve household dietary quality but may also increase their unpaid time needed for food shopping and cooking, especially if men believe this is women's sole responsibility. Therefore, nutrition education should be accompanied by a shift in attitudes. As Alderman et al. (2025) aptly note, "*Men can cook*." Effective policy interventions must be holistic, relying on cross-sectoral discussion and coordination, for example, between health, agriculture, labor, and education departments.

Next, although our findings show multidimensional benefits of supermarket expansion in China, policy should prioritize building sustainable, modern, and healthy food environments rather than merely promoting supermarkets. Governments sometimes offer supermarkets tax incentives, subsidies, or land concessions to encourage expansion (Reardon et al., 2012). Yet, supermarkets alone cannot generate inclusive benefits unless they are part of an ecosystem that includes diverse producers and consumers, efficient value chains, and fair market competition. Accordingly, policymakers should aim for enabling infrastructures (e.g., roads, transportation links, electricity supply, and cold-chain logistics) and institutional supports (e.g., food safety regulations, nutrition labeling, and sugar tax). These interventions can encourage both traditional markets and supermarkets, improve market access for all farmers, and ensure that consumers benefit from improved quality and price competition.

Last but not least, there is a clear need for better systems to monitor and collect data on diets and market trends. One reason for the limited literature on supermarket effects is the scarcity of nationally representative data on where people shop and how they eat. While the CHNS team has made significant strides in tracking thousands of Chinese households through 24-hour recalls, its data collection is infrequent. Comparable initiatives, such as the LSMS-ISA (Living Standards Measurement Study - Integrated Surveys on Agriculture) program in Africa, rely on 7-day recall methods that may introduce greater reporting biases (Bajunaid et al., 2025). Such differences in data collection methods account for the current fragmented literature on the effects of supermarkets, with rare cross-country comparative analysis. In addition, dietary data are often not widely accessible. The CHNS data collected after 2015 remain restricted from public use. The open access to high-quality data is not only crucial for academic research but also for public education. When consumers are informed about dietary trends and health outcomes, they are more likely to make healthier choices. Therefore, a key policy recommendation is to build a robust data infrastructure on the model of the UK's National Diet and Nutrition Survey (DNDS) and the U.S. National Health and Nutrition Examination Survey (NHANES).

Finally, we hope that this dissertation offers some insights for policymakers in transforming agri-food systems in a way that leaves no one behind and achieves the ambitious vision of sustainable development.

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Appendix A: Appendix to Chapter 2

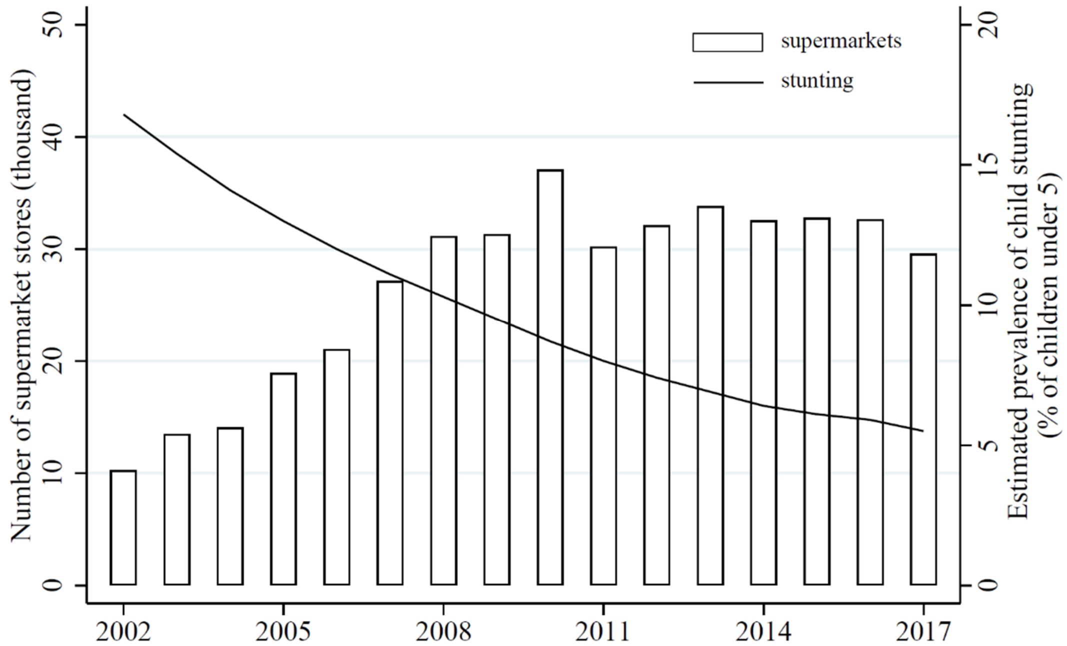

Fig. A1 Supermarket expansion and child stunting in China 2002-2017

Sources: Supermarket data from CEIC (https://www.ceicdata.com/en/china/supermarket), child stunting data from the World Bank (https://data.worldbank.org/country/china).

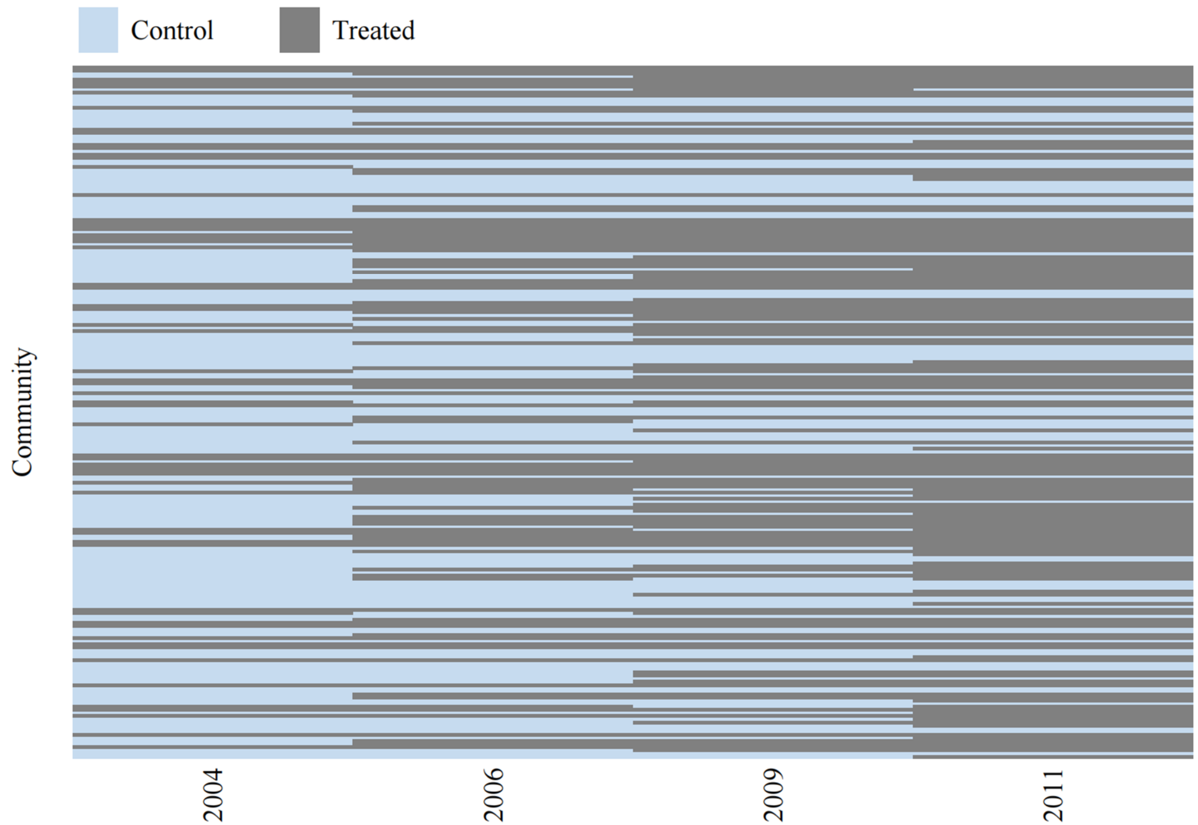

Fig. A2 Diffusion of supermarkets in each community from 2004 to 2011

Notes: The Figure visualizes the expansion of supermarkets in each surveyed community over time. Each horizontal line represents one community. The blue line segment and the gray line segment indicate the absence and presence of a supermarket in or near the community, respectively.

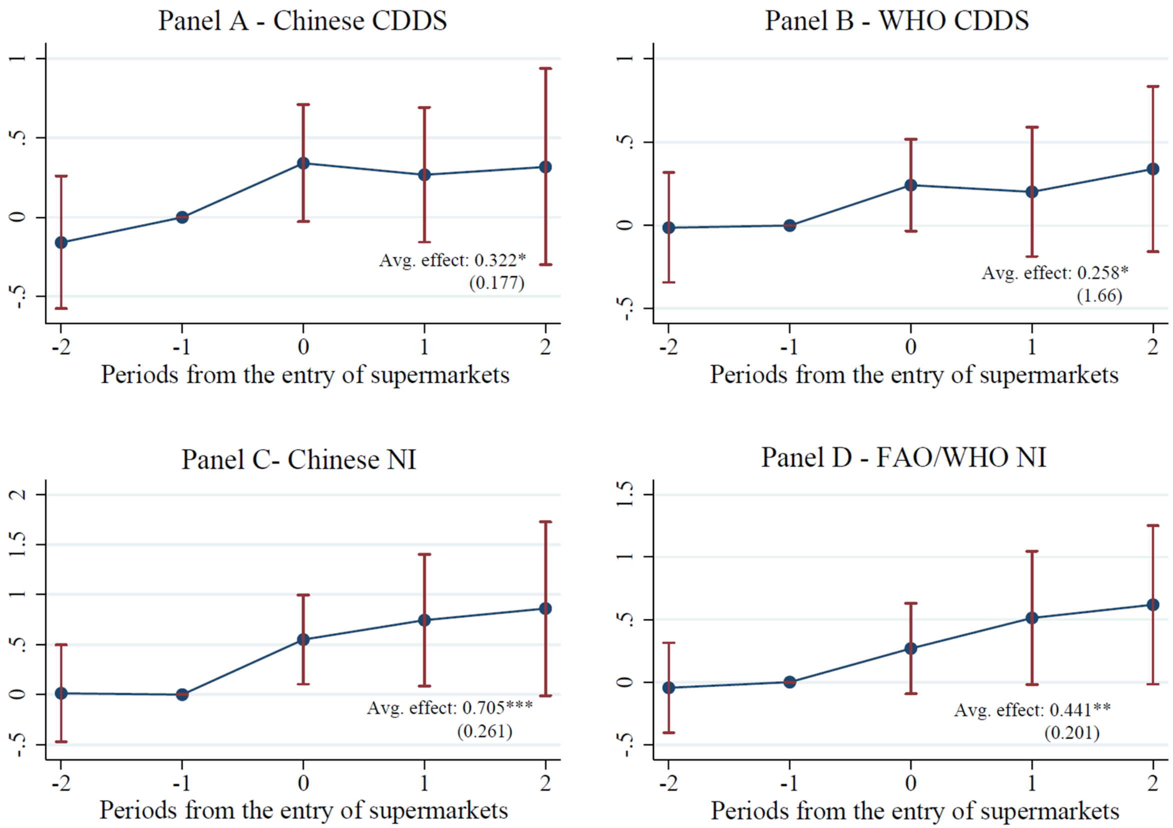

Fig. A3 Effects of supermarkets on child diets using a balanced panel (children included in all four survey waves)

Notes: The CDH estimator was used for the underlying regressions. The models include 891 child observations. *, **, and ** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the community-sex level.

Table A1 Questionnaire used to measure maternal dietary knowledge

Questions: Do you strongly agree, somewhat agree, somewhat disagree or strongly disagree with this statement?	Score 1 strongly disagree 2 disagree 3 neutral 4 agree 5 strongly agree 9 unknown
Choosing a diet with a lot of fresh fruits and vegetables is good for one's health.	a1
Eating a lot of sugar is good for one's health.	a2
Eating a variety of foods is good for one's health.	a3
Choosing a diet high in fat is good for one's health.	a4
Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health.	a5
Consuming a lot of animal products daily (fish, poultry, eggs, and lean meat) is good for one's health.	a6
Reducing the amount of fatty meat and animal fat in the diet is good for one's health.	a7
Consuming milk and dairy products is good for one's health.	a8
Consuming beans and bean products is good for one's health.	a9
The heavier one's body is, the healthier he or she is.	a10

Note: The final score for dietary knowledge is calculated as:

$$Dietary\ knowledge\ score = a1 + (6 - a2) + a3 + (6 - a4) + a5 + (6 - a6) + a7$$
$$+ a8 + a9 + (6 - a10)$$

If the answer is "9 unknown", we categorize it as "3 neutral."

Table A2 Definition of explanatory variables and descriptive statistics

Variable	Definition	Mean	SD
Individual child			
Age	Years of age	10.10	4.36
Edu	Years of education completed	4.32	3.60
Physical activity	Time (minutes) on physical activities each week	197.57	304.68
Household			
Ln(income)	Per capita household income inflated to 2011 prices	8.55	1.11
Edu_mother	Mother's years of education completed	7.57	4.18
Edu_father	Father's years of education completed	7.64	4.57
Dietary knowledge	Score for mother's dietary knowledge	35.66	3.35
Household size	Number of household members	4.47	1.43
Refrigerator	Does household own a refrigerator (dummy)?	0.56	0.50
Car	Does household own a car? (dummy)	0.09	0.29
Motorcycle	Does household own a motorcycle? (dummy)	0.41	0.49
Production diversity	Household number of farming activities (crop, fishing, gardening, livestock)	1.29	1.27
Community			
Supermarket access	Community has access to a supermarket within 5 km (dummy)	0.52	0.50
Traditional market	Community has traditional market within 5 km (dummy)	0.92	0.27
Chinese restaurant	Community has traditional restaurant within 5 km (dummy)	0.42	0.49
Fast-food restaurant	Community has fast-food restaurant within 5 km (dummy)	0.21	0.41
Bus stop	Community has a bus stop (dummy)	0.62	0.48

Note: Number of observations = 6,316.

Table A3 The matched DID approach (examples of selecting samples)

Individuals \ Waves	2004	2006	2009	2011	Sample selection
1		×	√		keep
2	×	×			keep
3		√	√		drop
4	×	×	√		keep in 2006 and 2009
5		×	√	√	keep in 2006 and 2009
6	√	√	√		drop
7	×	×	×	√	keep in 2009 and 2011
8	×	√	√	√	keep in 2004 and 2006
9	√	√	√	√	drop
10	×	×	×	×	randomly keep two consecutive waves

Note: "×" means the observation had no access to supermarkets in that year, and "√" means the opposite.

Further explanation: In the first step, we select samples from the unbalanced panel data to form a two-period balanced panel data with control groups and "treatment" groups. For children with only two consecutive observations in four waves, we keep those who have no access to supermarkets in the former wave and have access to supermarkets in the later wave or who have no access to supermarkets in both waves. For children with three consecutive observations in four waves, we only keep two consecutive observations. The former observation has no access to supermarkets, and the later observation has access to supermarkets; otherwise, we randomly select two consecutive observations if all three consecutive observations have no access to supermarkets. The sample selection method for children with four consecutive observations in four waves is the same as that of children with three consecutive observations. Table A3 visually demonstrates the sample selection method. Thus, all the selected samples have two observations in two periods. Then samples with no access to supermarkets in both periods are classified into control groups. Those having no access to supermarkets in the first period but access to supermarkets in the second period are the "treatment" groups. A total of 2,422 observations are selected for the following regressions.

In the second stage, we apply the kernel matching method to match samples based on individual, household, and regional variables in the first period to ensure that the treatment and control groups have similar characteristics except for supermarket accessibility. After matching, we use standard DID method to estimate the net effects of supermarket accessibility. Its principle is to compare the differences in the dependent variable between the treatment and control groups before and after supermarket access, and then conduct significant tests for the differences. The econometric model is as follows:

$$\text{Matched DID} = E[\, Y_{1i}^{t} - Y_{0i}^{t} \mid P(X_{0i}), T = 1] - E[Y_{1i}^{c} - Y_{0i}^{c} \mid P(X_{0i}), T = 0]$$

where Y_{0i}^{t} and Y_{1i}^{t} refer to dependent variables (i.e., dietary diversity and nutrition index) of treatment groups in two periods, and Y_{0i}^{c} and Y_{1i}^{c} refer to the outcome variables of control groups in two periods. $P(X_{0i})$ are the propensity scores according to individual, household, and regional characteristics. T equals one if the individual is in the treatment group; otherwise, T equals zero. Finally, standard errors are clustered at the community-sex level.

Table A4 Dietary diversity and nutrient intakes among Chinese children (2004-2011)

		2004	2006	2009	2011	Full sample
		(n = 1771)	(n = 1517)	(n = 1379)	(n = 1649)	(n = 6316)
Mean age	years	10.78	10.22	9.80	9.50	10.10
		(4.36)	(4.37)	(4.23)	(4.34)	(4.36)
Chinese CDDS	Score, range (0-9)	5.42	5.63	5.88	6.30	5.80
		(1.11)	(1.14)	(1.11)	(1.25)	(1.20)
WHO CDDS	Score, range (0-7)	3.71	3.91	4.11	4.43	4.03
		(0.95)	(0.98)	(0.92)	(1.03)	(1.01)
Chinese NI	Score, range (0-8)	4.60	4.48	4.53	4.49	4.53
		(1.25)	(1.24)	(1.22)	(1.33)	(1.26)
FAO/WHO NI	Score, range (0-8)	5.86	5.84	5.92	5.87	5.87
		(0.96)	(0.96)	(0.97)	(1.10)	(1.00)
Calorie	kcal/day	1697.31	1615.46	1557.46	1435.62	1578.79
		(652.78)	(628.20)	(598.54)	(550.90)	(617.47)
Protein	g/day	52.30	49.24	48.84	49.07	49.97
		(24.50)	(21.31)	(20.18)	(20.22)	(21.79)
Vitamin A	µg RE/day	305.22	304.51	335.86	386.89	333.06
		(378.80)	(449.07)	(375.85)	(360.21)	(393.05)
Vitamin C	mg/day	61.37	54.94	51.42	49.21	54.48
		(38.38)	(36.44)	(32.98)	(34.78)	(36.16)
Vitamin E	mg/day	3.43	3.20	3.16	2.94	3.19
		(2.41)	(2.38)	(2.28)	(2.32)	(2.36)
Calcium	mg/day	291.74	291.84	299.60	339.79	306.03

		(244.56)	(250.77)	(222.78)	(220.40)	(230.52)
Iron	mg/day	15.46	14.57	14.20	13.45	14.44
		(7.83)	(8.03)	(7.12)	(8.35)	(7.91)
Zinc	mg/day	8.56	7.93	7.77	7.26	7.90
		(3.82)	(3.55)	(3.32)	(3.25)	(3.54)
HAZ	Z-score	-0.72	-0.59	-0.34	-0.14	-0.45
		(1.22)	(1.26)	(1.20)	(1.35)	(1.28)
BAZ	Z-score	-0.23	-0.22	-0.21	0.11	-0.13
		(1.22)	(1.29)	(1.35)	(1.71)	(1.42)
Underweight	Dummy (0,1)	0.13	0.12	0.10	0.08	0.11
		(0.33)	(0.33)	(0.30)	(0.27)	(0.31)
Overweight	Dummy (0,1)	0.15	0.16	0.17	0.23	0.18
		(0.36)	(0.37)	(0.38)	(0.42)	(0.38)
Obesity	Dummy (0,1)	0.04	0.06	0.06	0.10	0.06
		(0.20)	(0.23)	(0.23)	(0.30)	(0.25)

Note: Mean values are shown with standard deviations in parentheses.

Table A5 Structure of energy sources of Chinese children (derived from the CHNS data)

			2004	2006	2009	2011
Carbohydrates		g/day	254.28	238.54	219.02	190.90
	share of energy	%	59.99%	58.82%	56.15%	52.52%
Protein		g/day	53.25	50.19	49.80	50.40
	share of energy	%	12.42%	12.33%	12.75%	13.95%
Fat		g/day	54.47	53.27	55.92	55.04
	share of energy	%	27.54%	28.77%	31.06%	33.45%

Table A6 DDS and NI in various groups (pooled sample)

	Urban	Rural	Diff.	Boys	Girls	Diff.	High income	Low income	Diff.	Younger	Older	Diff.
Chinese DDS	6.266	5.429	0. 837***	5.804	5.794	0.010	5.924	5.742	0.182***	5.888	5.764	0.124***
	(1.24)	(1.04)		(1.18)	(1.23)		(1.21)	(1.20)		(1.26)	(1.18)	
WHO DDS	4.434	3.716	0.718***	4.033	4.033	0.001	4.144	3.982	0.162***	4.070	4.019	0.052*
	(1.00)	(0.90)		(1.00)	(1.02)		(1.02)	(1.01)		(1.05)	(1.00)	
Chinese NI	4.744	4.358	0.387***	4.628	4.417	0.211***	4.651	4.472	0.179***	4.568	4.429	0.139***
	(1.31)	(1.19)		(1.25)	(1.27)		(1.28)	(1.25)		(1.22)	(1.36)	
FAO/WHO NI	6.023	5.748	0.276***	5.900	5.836	0.065**	5.953	5.831	0.122***	6.093	5.782	0.311***
	(1.03)	(0.96)		(0.98)	(1.03)		(0.98)	(1.01)		(1.02)	(0.98)	
N	2,793	3,523		3,348	2,968		2,001	4,315		1,781	4,535	

Notes: Mean values are shown with standard deviations in parentheses. We use *t*-tests to statistically compare mean differences. High-income and low-income households are classified by the mean per capita income of all households in each community. Younger and older children are those below and above 6 years, respectively. *** indicates significance at the 1% level.

Table A7 Effects of supermarkets on child dietary diversity (full TWFE results)

	Chinese CDDS			WHO CDDS		
	(1)	(2)	(3)	(4)	(5)	(6)
Supermarket	0.304***	0.187**	0.287***	0.304***	0.231***	0.280***
	(0.076)	(0.077)	(0.075)	(0.066)	(0.069)	(0.064)
Age	-0.337	-0.121	-0.776	-0.315*	-0.345	-0.418
	(0.261)	(0.351)	(0.510)	(0.184)	(0.273)	(0.413)
Edu	-0.009	-0.008	-0.006	-0.012	-0.009	-0.009
	(0.020)	(0.020)	(0.021)	(0.016)	(0.015)	(0.016)
Physical activity	0.000	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income)	0.011	0.007	0.012	0.013	0.008	0.016
	(0.023)	(0.022)	(0.024)	(0.019)	(0.019)	(0.019)
Edu_mother	0.013	0.013*	0.012	0.005	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)
Edu_ father	0.010	0.013*	0.010	0.014**	0.016***	0.014**
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Dietary knowledge	0.005	0.010	0.006	0.001	0.004	0.002
	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)
Household size	-0.039	-0.038	-0.038	-0.014	-0.013	-0.014
	(0.026)	(0.027)	(0.026)	(0.025)	(0.025)	(0.025)
Refrigerator	0.201***	0.139**	0.180***	0.186***	0.149***	0.170***
	(0.060)	(0.060)	(0.061)	(0.049)	(0.048)	(0.048)
Car	0.169	0.161	0.165	0.119	0.098	0.125*

	(0.105)	(0.102)	(0.107)	(0.073)	(0.075)	(0.073)
Motorcycle	0.128**	0.054	0.130**	0.073	0.021	0.074*
	(0.055)	(0.052)	(0.055)	(0.045)	(0.043)	(0.044)
Production diversity	0.059*	0.051	0.065**	0.016	0.010	0.018
	(0.031)	(0.032)	(0.032)	(0.026)	(0.027)	(0.026)
Free market	-0.110	-0.120*	-0.102	-0.119*	-0.140**	-0.145**
	(0.070)	(0.071)	(0.078)	(0.067)	(0.069)	(0.070)
Chinese restaurant	0.053	-0.099	0.113	0.022	-0.064	0.065
	(0.085)	(0.092)	(0.087)	(0.071)	(0.079)	(0.073)
Fast food restaurant	0.017	-0.036	0.002	0.083	0.081	0.084
	(0.069)	(0.077)	(0.072)	(0.057)	(0.061)	(0.060)
Bus stop	-0.031	-0.022	-0.023	0.042	0.058	0.029
	(0.060)	(0.057)	(0.060)	(0.045)	(0.042)	(0.043)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Year-by-region FE	No	Yes	No	No	Yes	No
Year-by-month FE	No	No	Yes	No	No	Yes
N	6,316	6,316	6,316	6,316	6,316	6,316

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the community-sex level in parentheses.

Table A8 Effects of supermarkets on child nutrition index (full TWFE results)

	Chinese NI			FAO/WHO NI		
Models	(1)	(2)	(3)	(4)	(5)	(6)
Supermarket	0.376***	0.349***	0.381***	0.279***	0.244***	0.278***
	(0.101)	(0.099)	(0.096)	(0.082)	(0.082)	(0.079)
Age	0.063	0.090	-1.295*	0.101	0.074	-0.913*
	(0.360)	(0.453)	(0.662)	(0.280)	(0.358)	(0.527)
Edu	-0.042	-0.035	-0.041	-0.078***	-0.073***	-0.080***
	(0.026)	(0.025)	(0.025)	(0.021)	(0.020)	(0.020)
Physical activity	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income)	0.018	0.018	0.022	0.034	0.034	0.035
	(0.030)	(0.030)	(0.030)	(0.024)	(0.024)	(0.024)
Edu_mother	-0.004	-0.002	-0.005	-0.008	-0.006	-0.008
	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)
Edu_ father	-0.008	-0.006	-0.008	-0.008	-0.006	-0.008
	(0.008)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)
Dietary knowledge	0.005	0.007	0.006	0.008	0.010	0.008
	(0.010)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
Household size	-0.088**	-0.078*	-0.081**	-0.066**	-0.059**	-0.062**
	(0.040)	(0.041)	(0.040)	(0.030)	(0.029)	(0.030)
Refrigerator	0.113	0.089	0.095	0.090	0.072	0.076
	(0.079)	(0.076)	(0.078)	(0.063)	(0.061)	(0.063)
Car	0.220*	0.174	0.239*	0.161	0.119	0.171*

	(0.131)	(0.132)	(0.130)	(0.104)	(0.106)	(0.103)
Motorcycle	0.104	0.051	0.086	0.085	0.042	0.079
	(0.069)	(0.068)	(0.068)	(0.056)	(0.055)	(0.055)
Production diversity	0.024	0.021	0.035	0.026	0.024	0.032
	(0.040)	(0.041)	(0.040)	(0.033)	(0.034)	(0.032)
Free market	-0.076	-0.026	-0.049	-0.025	0.010	-0.016
	(0.101)	(0.101)	(0.102)	(0.078)	(0.077)	(0.083)
Chinese restaurant	0.054	-0.047	0.137	0.116	0.028	0.172**
	(0.104)	(0.114)	(0.106)	(0.086)	(0.091)	(0.087)
Fast food restaurant	0.084	0.114	0.096	0.067	0.079	0.067
	(0.079)	(0.086)	(0.079)	(0.063)	(0.064)	(0.060)
Bus stop	0.095	0.158**	0.092	0.052	0.103*	0.060
	(0.074)	(0.073)	(0.072)	(0.056)	(0.057)	(0.056)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Year-by-region FE	No	Yes	No	No	Yes	No
Year-by-month FE	No	No	Yes	No	No	Yes
N	6,316	6,316	6,316	6,316	6,316	6,316

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the community-sex level in parentheses.

Table A9 Effects of supermarket closures

	Chinese CDDS	WHO CDDS	Chinese NI	FAO/WHO NI
	(1)	(2)	(3)	(4)
Supermarket	-0.006	-0.043	-0.683**	-0.307
	(0.196)	(0.176)	(0.312)	(0.273)
Controls	Yes	Yes	Yes	Yes
Individual and Year FEs	Yes	Yes	Yes	Yes
N	509	509	509	509

Notes: Estimates obtained with the CDH DID estimator. ** indicates significance at 5% level. Standard errors clustered at the community-sex level in parentheses.

Further explanation: In a small number of communities, supermarkets closed after a certain time of operation. We estimate effects of closure. The control group in this setting is communities that had a supermarket entry in the same year without later supermarket closure (de Chaisemartin and D'Haultfoeuille, 2024). While the relevant sample is small (only about 10 communities in the sample experienced supermarket closure), results show some evidence that the closure of supermarkets results in a decrease in dietary quality. The closure of supermarkets can be due to several factors, such as the decrease of consumers (population out-migration), the increase of competitors, and the incompatibility of business strategies with local consumption habits.

Table A10 Results with supermarket proximity as explanatory variable

	Chinese CDDS	WHO CDDS	Chinese NI	FAO/WHO NI
	(1)	(2)	(3)	(4)
Supermarket proximity	0.083***	0.088***	0.088**	0.062*
	(0.037)	(0.030)	(0.044)	(0.033)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year-by-region FE	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316

Notes: The TWFE estimator was used for these regressions. Due to imprecise measurement of the continuous proximity variable and its large variation from zero to infinity, the CDH is not a suitable estimator here (de Chaisemartin and D'Haultfoeille, 2024). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the community-sex level in parentheses.

Table A11 Regressions with standard errors clustered at the community level

	Chinese CDDS	WHO CDDS	Chinese NI	FAO/WHO NI
Models	(1)	(2)	(3)	(4)
Supermarket	0.175**	0.205***	0.258**	0.184**
	(0.08)	(0.07)	(0.11)	(0.08)
Control variables	Yes	Yes	Yes	Yes
Individual and year FEs	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316

Notes: The CDH estimator was used for these regressions. ** and *** indicate significance at the 5% and 1% level, respectively. Standard errors clustered at the community level in parentheses.

Table A12 Effects of supermarkets on calorie and nutrient intakes

	Calories	Protein	Vitamin A	Vitamin C	Vitamin E	Calcium	Iron	Zinc
Supermarket	92.297**	3.487**	-0.008	3.792	0.490***	41.288**	1.198**	0.684***
	(37.315)	(1.409)	(21.751)	(3.338)	(0.149)	(17.121)	(0.515)	(0.237)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316	6,316	6,316	6,316	6,316

Notes: The CDH estimator was used for these regressions. ** and *** indicate significance at the 5%, and 1% level, respectively. Standard errors clustered at the community-sex level are shown in parentheses.

Table A13 Association between the entry of supermarkets in period t and dietary variables in period t-1 (with individual fixed effects)

	Dependent variable: Supermarket (0,1)			
Chinese CDDS	-0.004			
	(0.008)			
WHO CDDS		-0.001		
		(0.009)		
Chinese NI			0.005	
			(0.006)	
FAO/WHO NI				0.008
				(0.007)
Age	-0.043	-0.044	-0.050	-0.043
	(0.246)	(0.246)	(0.245)	(0.246)
Edu	0.007	0.007	0.007	0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Physical activity	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income)	-0.013	-0.013	-0.013	-0.013
	(0.010)	(0.010)	(0.010)	(0.010)
Edu_mother	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Edu_ father	-0.000	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Dietary knowledge	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)

Household size	0.002	0.002	0.002	0.002
	(0.009)	(0.009)	(0.009)	(0.009)
Refrigerator	-0.004	-0.004	-0.004	-0.004
	(0.026)	(0.026)	(0.026)	(0.026)
Car	0.031	0.031	0.031	0.031
	(0.033)	(0.033)	(0.033)	(0.033)
Motorcycle	-0.000	-0.000	-0.001	-0.000
	(0.021)	(0.021)	(0.021)	(0.021)
Production diversity	-0.016	-0.016	-0.017	-0.016
	(0.012)	(0.012)	(0.012)	(0.012)
Free market	-0.045	-0.045	-0.045	-0.045
	(0.072)	(0.071)	(0.072)	(0.072)
Chinese restaurant	0.077	0.078	0.078	0.077
	(0.117)	(0.117)	(0.117)	(0.117)
Fast food restaurant	-0.205***	-0.205***	-0.206***	-0.205***
	(0.049)	(0.049)	(0.049)	(0.049)
Bus stop	-0.011	-0.010	-0.011	-0.011
	(0.047)	(0.047)	(0.047)	(0.047)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year-by-region FE	Yes	Yes	Yes	Yes
N	4,667	4,667	4,667	4,667

Notes: The TWFE estimator was used for these regressions. Standard errors clustered at the community level in parentheses. *** indicate significance at the 1% level.

Table A14 Association between the entry of supermarkets in period t and dietary variables in period t-1 (with household fixed effects)

	Dependent variable: Supermarket (0,1)			
Chinese CDDS	-0.004			
	(0.008)			
WHO CDDS		0.001		
		(0.009)		
Chinese NI			0.007	
			(0.006)	
FAO/WHO NI				0.010
				(0.007)
Age	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Edu	0.002	0.002	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Physical activity	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income)	-0.014	-0.014	-0.014	-0.014
	(0.011)	(0.011)	(0.011)	(0.011)
Edu_mother	0.000	-0.000	0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Edu_ father	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Dietary knowledge	0.002	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)

Household size	-0.001	-0.001	-0.001	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)
Refrigerator	-0.012	-0.012	-0.013	-0.013
	(0.025)	(0.024)	(0.025)	(0.025)
Car	0.024	0.023	0.023	0.023
	(0.029)	(0.029)	(0.030)	(0.029)
Motorcycle	-0.002	-0.002	-0.003	-0.003
	(0.020)	(0.020)	(0.020)	(0.020)
Production diversity	-0.012	-0.013	-0.013	-0.013
	(0.011)	(0.011)	(0.011)	(0.011)
Free market	-0.050	-0.050	-0.051	-0.051
	(0.072)	(0.072)	(0.072)	(0.072)
Chinese restaurant	0.064	0.064	0.065	0.065
	(0.119)	(0.119)	(0.119)	(0.119)
Fast food restaurant	-0.204***	-0.204***	-0.206***	-0.207***
	(0.051)	(0.051)	(0.050)	(0.050)
Bus stop	-0.012	-0.012	-0.013	-0.013
	(0.045)	(0.045)	(0.045)	(0.045)
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year-by-region FE	Yes	Yes	Yes	Yes
N	4,667	4,667	4,667	4,667

Notes: The TWFE estimator was used for these regressions. Standard errors clustered at the community level in parentheses. *** indicate significance at the 1% level.

Table A15 Effects of supermarkets on nutrient intakes at home and away from home

	Calorie	Protein	Vitamin A	Vitamin C	Vitamin E	Calcium	Iron	Zinc
Panel A: At home								
Supermarket	78.054	2.958*	-5.346	2.832	0.431***	55.437***	0.805	0.456*
	(52.66)	(1.62)	(26.45)	(3.24)	(0.153)	(27.00)	(0.53)	(0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316	6,316	6,316	6,316	6,316
Panel B: Away from home								
Supermarket	14.244	0.528	3.181	0.960	0.058	-14.149	0.393	0.228*
	(45.81)	(0.88)	(11.63)	(0.72)	(0.07)	(13.50)	(0.27)	(0.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316	6,316	6,316	6,316	6,316

Notes: The CDH estimator was used for these reressions. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the community-sex level in parentheses.

Table A16 Effects of supermarkets among households with and without refrigerator

	Households without refrigerator				Households with refrigerator			
	Chinese CDDS	WHO CDDS	Chinese NI	FAO/ WHO NI	Chinese CDDS	WHO CDDS	Chinese NI	FAO/ WHO NI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supermarket	0.191**	0.267**	0.381**	0.257**	0.244**	0.229***	0.299**	0.274**
	(0.091)	(0.112)	(0.166)	(0.114)	(0.105)	(0.074)	(0.134)	(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,774	2,774	2,774	2,774	3,542	3,542	3,542	3,542

Notes: The CDH estimator was used for these regressions. ** and *** indicate significance at the 5% and 1% level, respectively. Standard errors are clustered at the community level.

Table A17 Effects of supermarkets on households owning a refrigerator

	Dependent variable: Refrigerator (0,1)	
	TWFE	CDH
	(1)	(2)
Supermarket	-0.009	-0.043
	(0.023)	(0.028)
Controls	Yes	Yes
Household and year FEs	Yes	Yes
N	5,420	5,420

Note: Standard errors are clustered at the community level.

Table A18 Heterogeneous effects of supermarkets on body weight and height

	Boys	Girls	Younger	Older	Low income	High income	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: HAZ								
Supermarket	0.102*	0.042	0.157	0.110*	-0.008	0.495	0.087	0.087*
	(0.053)	(0.066)	(0.208)	(0.066)	(0.062)	(0.376)	(0.093)	(0.046)
Panel B: BAZ								
Supermarket	0.109	-0.040	-0.050	0.060	0.0001	0.129	-0.134	0.058
	(0.107)	(0.082)	(0.223)	(0.078)	(0.092)	(0.328)	(0.123)	(0.067)
Panel C: Underweight								
Supermarket	0.008	0.001	0.043	-0.007	0.004	-0.002	0.053	-0.007
	(0.022)	(0.019)	(0.051)	(0.016)	(0.017)	(0.110)	(0.048)	(0.011)
Panel D: Overweight								
Supermarket	0.065	0.004	0.008	0.027	0.050	0.084	0.072	-0.003
	(0.040)	(0.024)	(0.069)	(0.025)	(0.037)	(0.088)	(0.049)	(0.018)
Panel E: Obesity								
Supermarket	-0.006	0.002	-0.041	0.007	-0.001	-0.004	-0.060	0.016
	(0.022)	(0.019)	(0.042)	(0.016)	(0.016)	(0.118)	(0.037)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The CDH estimator was used for these regressions, except for columns (3)-(4), which are based on the TWFE estimator due to subsample size. * and ** indicate significance at 10% and 5% levels, respectively. Standard errors clustered at the community-sex level are in parentheses.

Testing for Attrition Bias

To assess whether sample attrition may cause bias, we use the following two-way fixed effects model:

$$Attrition_{it} = \beta_0 + \varphi Y_{it} + \beta SM_{it} + \gamma X_{it} + u_{it}$$

where $Attrition_{it}$ is a dummy variable indicating whether the child drops out at the next survey wave; Y_{it} refers to the dietary indicators (i.e., DDS and NI), SM_{it} to supermarket access, and X_{it} to other controls. We use two-way fixed effects (TWFE) estimators with individual and time fixed effects. Results are shown in Table B1. They show that attrition is not correlated with child diets and the presence of supermarkets, nor is it significantly related to most of the controls. Hence, we do not expect any attrition bias in our estimates.

Table A19: Results of attrition analysis

	Dep. Var.: $Attrition_{it}$			
Models	(1)	(2)	(3)	(4)
Chinese CDDS	-0.012			
	(0.009)			
WHO CDDS		-0.006		
		(0.010)		
Chinese NI			-0.010	
			(0.007)	
FAO/WHO NI				-0.008
				(0.008)
Supermarket	-0.025	-0.025	-0.023	-0.025
	(0.030)	(0.030)	(0.030)	(0.030)
Age	-0.037	-0.038	-0.035	-0.035
	(0.143)	(0.143)	(0.142)	(0.142)

Edu	-0.002	-0.002	-0.002	-0.002
	(0.008)	(0.008)	(0.008)	(0.008)
Physical activity	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(income)	-0.015	-0.015	-0.015	-0.015
	(0.010)	(0.010)	(0.010)	(0.010)
Edu_mother	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Edu_ father	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Dietary knowledge	0.005^{*}	0.005^{*}	0.005^{*}	0.005^{*}
	(0.003)	(0.003)	(0.003)	(0.003)
Household size	0.015	0.015	0.015	0.015
	(0.012)	(0.012)	(0.012)	(0.012)
Refrigerator	-0.019	-0.019	-0.019	-0.020
	(0.024)	(0.024)	(0.023)	(0.023)
Car	0.000	-0.001	0.000	-0.000
	(0.031)	(0.031)	(0.031)	(0.031)
Motorcycle	-0.002	-0.002	-0.002	-0.002
	(0.018)	(0.018)	(0.018)	(0.018)
Production diversity	0.001	0.001	0.001	0.001
	(0.015)	(0.015)	(0.015)	(0.015)
Free market	0.009	0.010	0.010	0.011
	(0.034)	(0.034)	(0.034)	(0.034)

Chinese restaurant	0.062	0.063	0.063	0.064
	(0.043)	(0.043)	(0.043)	(0.043)
Fast food restaurant	0.090***	0.091***	0.092***	0.091***
	(0.030)	(0.030)	(0.030)	(0.030)
Bus stop	0.036	0.036	0.038	0.037
	(0.024)	(0.024)	(0.024)	(0.024)
Individual FE	Yes	Yes	Yes	Yes
Year-by-region FE	Yes	Yes	Yes	Yes
N	6,316	6,316	6,316	6,316

Notes: The TWFE estimator was used for these regressions. * and *** indicate significance at 10% and 1% levels, respectively. Standard errors clustered at the community-sex level in parentheses.

Appendix B: Appendix to Chapter 3

Table B1 The matrix for calculating CFPS sub-scores based on the Chinese Dietary Guidelines

Score \ Food group	Grains, roots, and tubers combined	Vegetables	Fruits	Meat, poultry, aquatic products, and egg combined	Milk and its products	Legumes and nuts	Edible oil	Salt
0	0-125	0-150	0-100	0-60	0-150	0-12.5	0-12.5	/
0.5	125-250	150-300	100-200	60-120	150-300	12.5-25	12.5-25	/
1	250-400	300-500	200-350	120-200	300-500	25-35	25-30	0-5
0.5	400-600	500-750	350-525	200-300	500-750	35-52.5	30-45	/
0	>600	>750	>525	>300	>750	>52.5	>45	>5

Notes: Data are from the Chinese Food Guide Pagoda (2022) (Available at http://dg.cnsoc.org/article/04/RMAbPdrjQ6CGWTwmo62hQg.html). Unit: Grams per day per person.

Table B2 Definition and descriptive statistics of all variables

Variable	Definition	Mean	SD
Dependent variables			
Time for cooking	Minutes spent per day by women for cooking food	79.2	45.4
Time for shopping	Minutes spent per day by women for shopping food	31.1	20.5
DDS	Individual dietary diversity score, range (0-9)	3.9	1.1
CFPS	Individual Chinese Food Pagoda Score, range (0-8)	2.5	1.0
DNDS	Individual Dietary Nutrient Density Score, range (-100-900)	34.3	10.7
Energy	Daily intake of calories (unit: kcal/per day)	2097.0	651.4
Energy intake from unprocessed foods	3-day average intake of calories from unprocessed foods (unit: kcal/per day)	1294.1	656.9
Energy intake from moderately processed foods	3-day average intake of calories from moderately processed foods (unit: kcal/per day)	672.4	424.0
Energy intake from highly processed foods	3-day average intake of calories from highly processed foods (unit: kcal/per day)	122.8	210.5
Protein	3-day average intake of protein (unit: grams/per day)	65.9	23.0
Protein intake from unprocessed foods	3-day average intake of protein from unprocessed foods (unit: grams/per day)	47.5	21.2
Protein intake from moderately processed foods	3-day average intake of protein from moderately processed foods (unit: grams/per day)	12.0	13.0
Protein intake from highly processed foods	3-day average intake of protein from highly processed foods (unit: grams/per day)	4.9	7.2
Fat	3-day average intake of fat (unit: grams/per day)	71.4	36.1
Fat intake from unprocessed foods	3-day average intake of fat from unprocessed foods (unit: grams/per day)	45.4	22.5
Fat intake from moderately processed foods	3-day average intake of fat from moderately processed foods (unit: grams/per day)	12.1	14.3
Fat intake from highly processed foods	3-day average intake of fat from highly processed foods (unit: grams/per day)	6.0	10.8
Carbohydrates	3-day average intake of carbohydrates (unit: grams/per day)	292.5	110.3
Carbohydrates intake from unprocessed	3-day average intake of carbohydrates from unprocessed foods (unit: grams/per	222.0	130.4

foods	day)		
Carbohydrates intake from moderately processed foods	3-day average intake of carbohydrates from moderately processed foods (unit: grams/per day)	59.5	67.4
Carbohydrates intake from highly processed foods	3-day average intake of carbohydrates from highly processed foods (unit: grams/per day)	10.0	20.9
BMI	Body mass index = kg/m^2 where kg is a person's weight in kilograms and m^2 is the height in meters squared	23.5	3.7
Overweight	1 if BMI ≥ 25 and 0 if not	0.3	0.5
Obesity	1 if BMI ≥ 30 and 0 if not	0.04	0.2
Key independent variable			
Access to supermarkets	1 if have access to supermarkets within 5 km and 0 if not	0.5	0.5
Control variables			
Age	Years of age	47.9	13.7
Income	Per capita household income (CNY) inflated to 2011 prices, used in log form in all regressions	12864.3	21378.5
Physical activity	Intensity of activity at work, on a scale of 1 to 5 from very slight activity to very heavy activity	2.6	1.2
Dietary knowledge	Score for individual dietary knowledge (see Supplementary Table S4)	36.1	3.5
Family size	Number of family members	3.7	1.5
Production diversity	Families' number of farming activities (crop farming, fishing, gardening, and livestock), range (0-4)	1.3	1.3
Economic activity	Aggregated index indicating typical daily wage for ordinary male worker and percent of the populations engaged in non-agricultural work (See Jones-Smith and Popkin (2010))	6.5	3.2
Car	Does household own a car? 1 if yes and 0 if no	0.1	0.3
Motorcycle	Does household own a motorcycle? 1 if yes and 0 if no	0.3	0.5
Refrigerator	Does household own a refrigerator? 1 if yes and 0 if no	0.6	0.5
Microwave	Does household own a microwave? 1 if yes and 0 if no	0.3	0.5

Pressure cooker	Does household own a pressure cooker? 1 if yes and 0 if no	0.5	0.5
Traditional food market	Aggregated index indicting the access (distance) to traditional food markets and number of days of operation (See Jones-Smith and Popkin (2010))	4.6	3.6
Chinese restaurant	Are there any restaurants in or near this community? 1 if yes and 0 if no	0.7	0.5

Note: The measurement of individual dietary knowledge is provided in Table B3.

The CHNS designed ten questions to analyze individual's dietary knowledge, as shown in the following table. Please note that the questions are asking about knowledge/attitudes, not about actual eating behavior. If the answer is "9 unknown", we consider it as "3 neutral". The final score for dietary knowledge is calculated using this equation:

$$Dietary\ knowledge\ score = a1 + (6 - a2) + a3 + (6 - a4) + a5 + (6 - a6) + a7 + a8 + a9 + (6 - a10)$$

Table B3 Questions for calculating dietary knowledge

Questions: Do you strongly agree, somewhat agree, somewhat disagree or strongly disagree with this statement?	Score 1 Strongly disagree 2 Disagree 3 Neutral 4 Agree 5 Strongly agree 9 Unknown
Choosing a diet with a lot of fresh fruits and vegetables is good for one's health.	a1
Eating a lot of sugar is good for one's health.	a2
Eating a variety of foods is good for one's health.	a3
Choosing a diet high in fat is good for one's health.	a4
Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health.	a5
Consuming a lot of animal products daily (fish, poultry, eggs, and lean meat) is good for one's health.	a6
Reducing the amount of fatty meat and animal fat in the diet is good for one's health.	a7
Consuming milk and dairy products is good for one's health.	a8
Consuming beans and bean products is good for one's health.	a9
The heavier one's body is, the healthier he or she is.	a10

Table B4 Classifications of unprocessed, moderately processed, and highly processed foods

Category	Definition	Example
Unprocessed foods	Unprocessed foods are those that are consumed in their natural state, with minimal alteration. Sometimes they undergo basic preparations, such as washing, peeling, cutting, portioning, or packaging, but these actions do not significantly change the inherent properties of the food. These foods are usually single-ingredient items that may have certain components removed, but no additives or artificial substances are introduced. Most unprocessed foods are perishable and require careful handling and storage. They are commonly found in traditional markets, such as wet markets, and, except for certain fruits and vegetables, often require cooking before consumption.	Fresh vegetables, fruits, wheat, rice, fresh meat and poultry, eggs, fresh milk, legumes, etc.
Moderately processed foods	Moderately processed foods are those that have undergone various processing techniques such as extraction, pressing, clarification, refining, purification, and grinding. Despite these processes, the foods still retain recognizable characteristics of their original plant or animal sources and are typically single-ingredient products without the mixing of multiple food components. The primary purpose of processing is to remove inedible parts, reduce spoilage, increase convenience of purchase and consumption, and improve nutritional quality and freshness. Although some flavor additives (sweeteners, salt, or flavors) may be used, they are often not added at the expense of nutritional value or consumer health. These foods also often have a relatively short shelf life. Some foods that have a long shelf life but are not usually consumed by themselves, such as honey and animal fats, are also included in this category.	Noodles, whole wheat bread, precooked grains, steamed bun, instant rice, corn products (including tortillas), soy products such as dried tofu, vegetable oils, animal fats (including lard and butter), dairy products such as yogurt, canned fruits or vegetables without additional flavoring, meat and fish cooked from raw/fresh ingredients or vacuum-packed, deep-frozen, etc.
Highly processed foods	Highly processed foods are industrially prepared foods, often including those from catering outlets, that require minimal domestic preparation, sometimes limited to heating. These foods are made from industrial ingredients, substances derived from food, or even laboratory-created compounds, and generally contain little to no whole food components. In other words, highly processed foods are multi-ingredient mixtures that are heavily altered from their original plant or animal sources. They often undergo secondary processing to become ready-to-eat, and are characterized by high levels of added sugars, fats, or salt, resulting in strong, distinct flavors. These foods are typically packaged for convenience, with a focus on consumer appeal, sometimes designed to be visually attractive or even to encourage “secondary consumption” outside of regular mealtime. They often have a long shelf life and are not commonly found in traditional wet markets. Condiments such as ketchup and soy sauce are also included in this category.	Packaged snacks (e.g., potato chips, cookies, candy bars, chocolate), processed meats (e.g., sausages, bacon, deli meats), frozen meals (pre-packaged with various ingredients and additives), soft drinks and sugary beverages, alcohol, fast food items (e.g., hamburgers, French fries, chicken nuggets), spices, chili oil, fat spreads and shortenings, refined grain bread, etc.

Note: The classification of foods by processing level in this table is based on the framework and key concepts derived from de Araújo et al. (2022), where the authors provide a comprehensive review of food processing categories. Our classification reflects a synthesis of the existing classification systems and is adapted to fit the China context of this study.

Reference:

de Araújo, T. P., de Moraes, M. M., Afonso, C., Santos, C., & Rodrigues, S. S. P. (2022). Food Processing: Comparison of Different Food Classification Systems. *Nutrients*, 14(4), 729. https://doi.org/10.3390/nu14040729

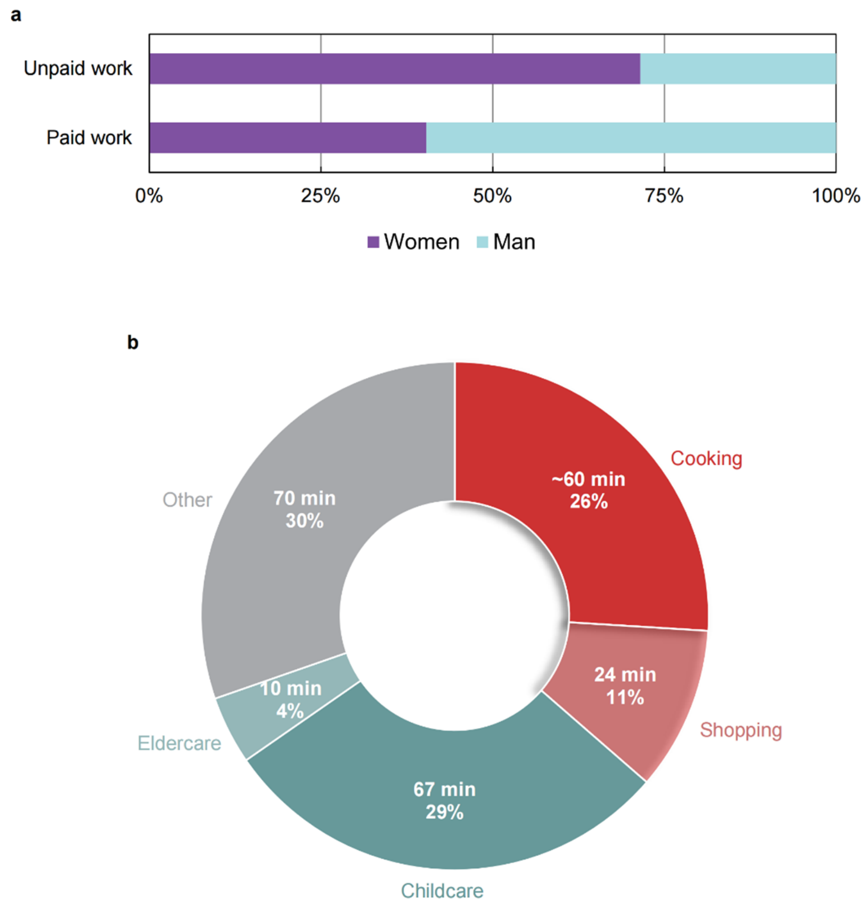

Fig. B1 Gendered time allocation in China

Notes: **a**, Work distribution measured by time use of men and women in 2018. **b**, Women's time allocation for unpaid activities in 2018. Data are from the National Time Use Survey conducted by the National Bureau of Statistics of China (NBSC) in 2018 (available at https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900224.html).

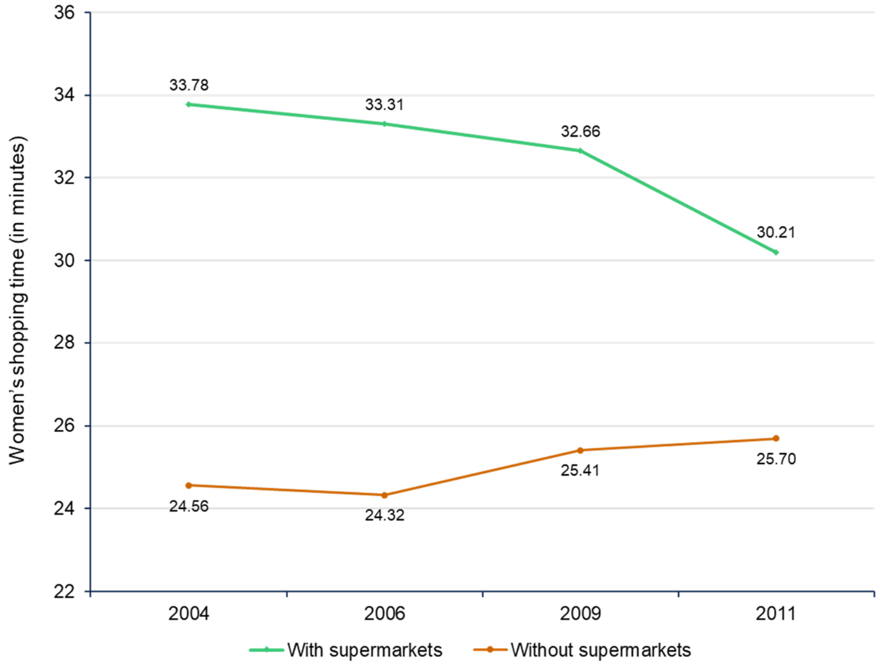

Fig. B2 Trends in average food shopping time among women with and without access to supermarkets within 5km in China

Note: Data are from the CHNS. The province fixed effect is controlled for.

Table B5 Structural change in infrastructure, employment, and food services at the community level in China

Variable	Definition	1989	1991	1993	1997	2000	2004	2006	2009	2011
		Mean								
Road	The type of road near the neighborhood/village: 1 if unpaved dirt road, 2 if gravel road, and 3 if concrete or asphalt road.	2.25	2.24	2.32	2.31	2.48	2.62	2.68	2.82	2.86
Electricity	The number of hours per day that electricity is available in the neighborhood/village.	17.47	20.85	22.3	22.53	23.02	23.71	23.9	23.86	23.88
Clean water	1 if the household has access to clean drinking water supplied by a water treatment plant through a piped system; 0 otherwise.	0.34	0.40	0.39	0.48	0.48	0.50	0.55	0.58	0.66
Non-agricultural employment	The percentage of the neighborhood/village labor force engaged in non-agricultural income-generating activities.	59.27	52.06	55.29	56.57	57.38	65.54	67.68	66.68	75.47
Out-of- neighborhood/village employment	The percentage of the workforce who work outside their neighborhood/village for at least one month per year, in locations such as nearby towns, counties or cities.	18.72	17.35	19.39	21.46	25.06	29.22	29.36	31.54	36.77
Traditional food markets	An aggregated index measuring the distance to traditional markets and the number of days of operation per week (See Jones-Smith and Popkin (2010) for details).	4.66	4.55	4.36	5.12	5.96	5.11	4.86	4.88	4.87
Refrigerator	Does household own a refrigerator? 1 if yes and 0 if no	n.a.	0.17	0.21	0.31	0.39	0.45	0.51	0.67	0.82
Microwave	Does household own a microwave? 1 if yes and 0 if no	n.a.	0.002	0.005	0.02	0.06	0.16	0.20	0.27	0.40
Pressure cooker	Does household own a pressure cooker? 1 if yes and 0 if no	n.a.	0.25	0.28	0.37	0.43	0.44	0.47	0.50	0.54
Supermarkets	The percentage of the neighborhood/village having access to a supermarket within 5 km.	n.a.	n.a.	n.a.	n.a.	n.a.	29.09	35.65	58.01	74.67

Note: Data are from the CHNS. n.a. means data not available because variables were not included in the respective survey rounds.

Table B6 Robustness checks

	Women who take the main responsibility for shopping and cooking		Men	
	(1) Ln (Shopping time)	(2) Ln (Cooking time)	(3) Shopping time	(4) Cooking time
Supermarket	-0.2545**	-0.2322**	-3.7233	-0.3901
	(0.1243)	(0.0976)	(2.9967)	(2.4512)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
N	4,914	4,968	4,701	4,701

Note: Estimated effects of supermarkets are shown with robust standard errors clustered at the community level in parentheses. Coefficients in columns (1)-(2) can be interpreted in percentage terms. Coefficients in columns (3)-(4) are interpreted in terms of minutes, as there are many zero values of men's time spent on shopping and cooking and the logarithm of zero is not defined. ** indicates statistical significance at the 5% level.

Table B7 Impact of supermarkets on energy and protein intake among adults with and without sufficient intake

	Dependent variable: Energy (kcal per day)	
	(1) Inadequate intake	(2) Adequate intake
Supermarket	-42.9088	-212.7771***
	(103.1411)	(80.5389)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	3,440	7,368
	Dependent variable: Protein (Grams per day)	
	(3) Inadequate intake	(4) Adequate intake
Supermarket	0.6095	-5.1391
	(2.1839)	(3.2206)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	4,283	6,525

Notes: Estimated effects of supermarkets from DID models are shown with robust standard errors clustered at the community-sex level in parentheses. We define inadequate and adequate intake based on the Dietary Reference Intakes for Chinese Residents (2013 Edition) (Available at https://www.chinanutri.cn/xxzy/xxzydybgsj/201506/t20150603_115510.html). Inadequate refers to an average intake across the four survey waves below the estimated energy requirement (EER) for energy and the recommended nutrient intake (RNI) for protein. Conversely, adequate refers to an average intake exceeding the EER for energy and the RNI for protein.

Table B8 Impact of supermarkets on the share of energy intake from fat

	(1) Share of energy intake from fat (range, 0-1)	(2) Dummy variable: share of energy intake from fat exceeds 30%
Supermarket	0.0429***	0.1041**
	(0.0119)	(0.0468)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	10,808	10,808

Note: Estimated effects of supermarkets from DID models are shown with robust standard errors clustered at the community-sex level in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

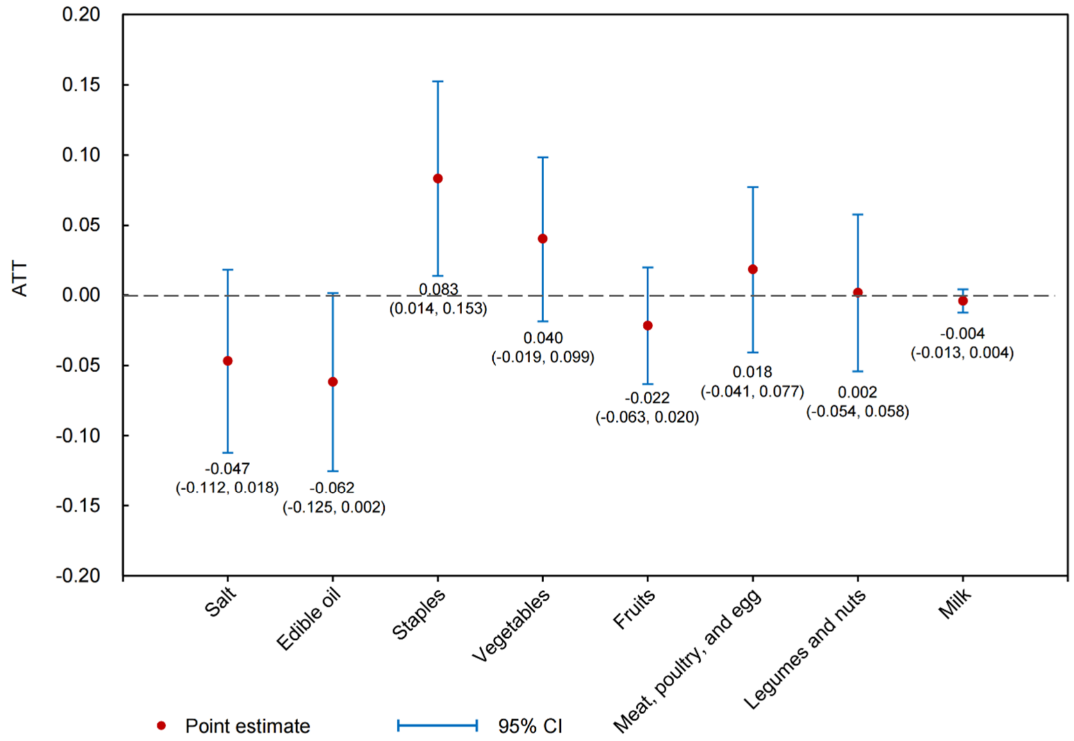

Fig. B3 Impacts of supermarkets on sub-scores of the CFPS

Notes: Each score, ranging from 0 to 1, measures the alignment of each food group with the recommended amount. A positive coefficient means that supermarkets are bringing actual intakes closer to recommended levels, and vice versa.

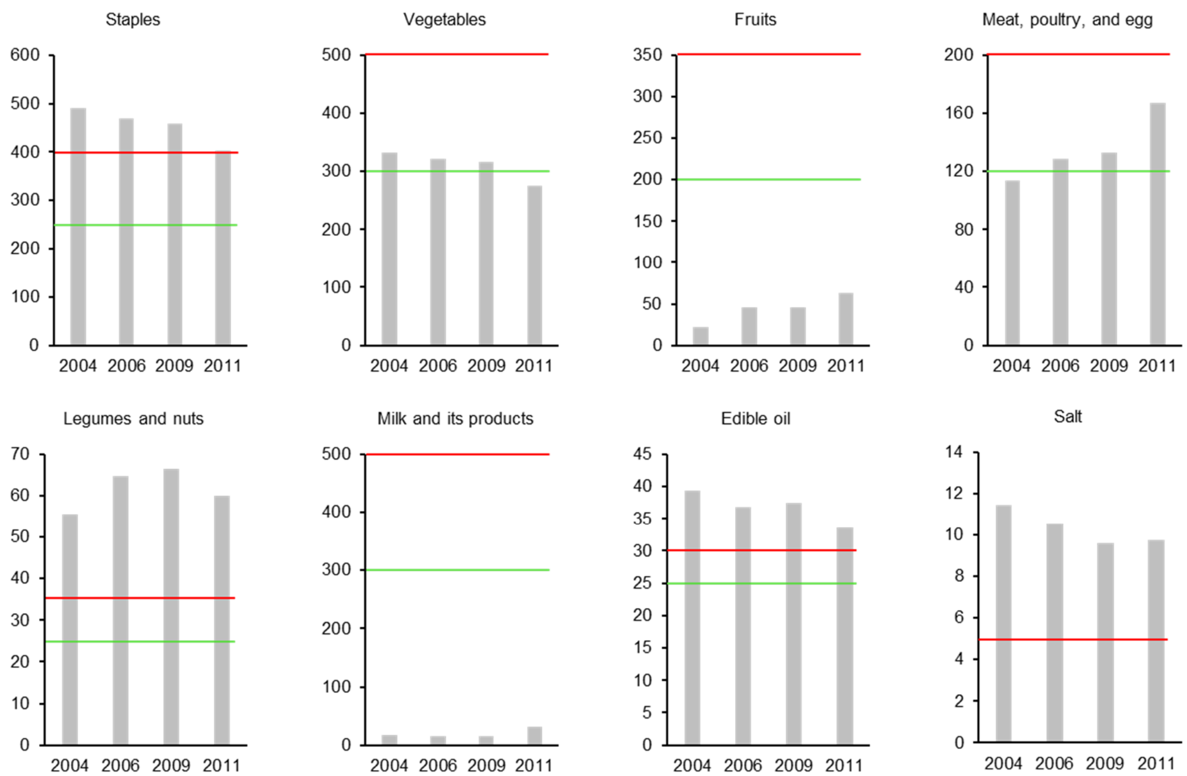

Fig. B4 Daily consumption (grams) of different food groups by Chinese adults (2004-2011)

Notes: The horizontal green lines indicate the recommended lower bound, and the red lines represent the upper bound according to the Chinese dietary guidelines.

Table B9 Impacts of supermarkets on nutritional outcomes

	(1) Full sample	(2) Women	(3) Men	(4) Low income	(5) High income	(6) Inadequate energy intake	(7) Adequate energy intake
Dependent variable: BMI							
Supermarket	0.0695	-0.0128	0.2101	0.2386	-0.0837	0.1487	-0.0049
	(0.1178)	(0.1320)	(0.2022)	(0.1754)	(0.2065)	(0.3613)	(0.1412)
Dependent variable: Overweight							
Supermarket	0.0145	-0.0038	0.0424	0.0221	-0.0044	0.0426	0.0199
	(0.0222)	(0.0288)	(0.0363)	(0.0330)	(0.0283)	(0.0738)	(0.0293)
Dependent variable: Obesity							
Supermarket	-0.0011	0.0027	-0.0065	0.0055	-0.0106	-0.0080	-0.0026
	(0.0087)	(0.0128)	(0.0103)	(0.0124)	(0.0115)	(0.0392)	(0.0081)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,212	5,823	4,389	5,092	5,120	3,226	6,986

Note: Estimated effects of supermarkets from DID models are shown with robust standard errors clustered at the community-sex level in parentheses.

Table B10 Impacts of supermarkets on women's time allocated for paid work, other unpaid chores, leisure, and sleeping

	Participation in paid work (dummy variables)		Ln Time for paid work among those already working		Ln Time for housework other than meal preparation	Ln Time for leisure	Ln Time for sleeping
	(1)	(2) Age≤55	(3)	(4) Age≤55	(5)	(6)	(7)
Supermarket	0.0508	0.1722**	0.0363	0.0060	-0.0450	0.1890*	0.0114
	(0.0466)	(0.0742)	(0.0815)	(0.0838)	(0.0395)	(0.1145)	(0.0120)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,822	4,283	3,968	3,219	5,822	5,822	5,822

Note: Estimated effects of supermarkets from DID models are shown with robust standard errors clustered at the community level in parentheses. Models (1) and (5)-(7) use the full sample of women. Model (3) includes only women who are already engaged in paid work to avoid estimation bias from observations with zero values. Models (2) and (4) include only women aged 55 years and below. * and ** denote statistical significance at the 10% and 5% levels, respectively.

Appendix C: Appendix to Chapter 4

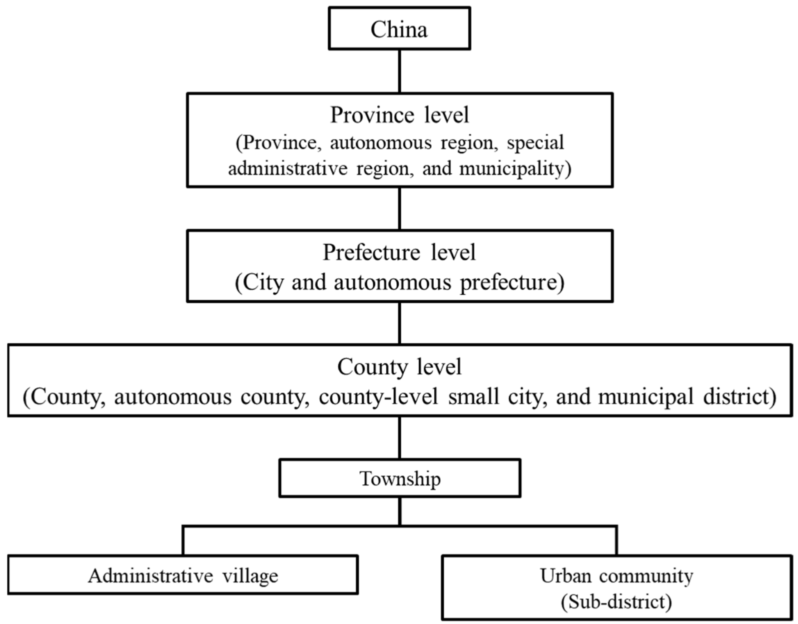

Fig. C1 Administrative hierarchy in China.

Source: The Stata Council of China (Available online: https://www.gov.cn/guoqing/2005-09/13/content_5043917.htm)

Further explanation: Fig. C1 shows the administrative hierarchy in China. We define supermarket expansion as the number of supermarket stores in rural areas within a given county and year. Rural areas are defined as those towns that include at least two villages. Figure S2 provides an example of how to differentiate rural and urban towns

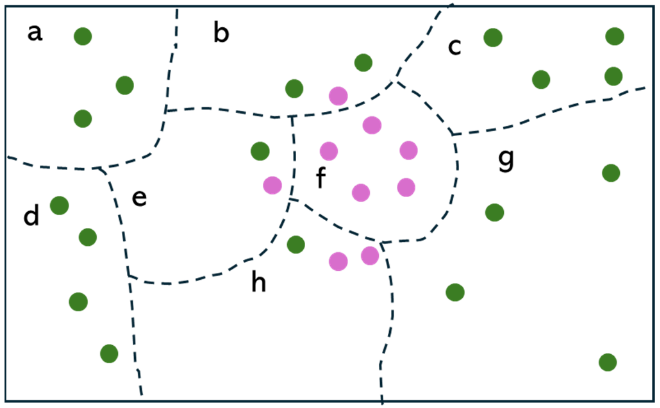

Fig. C2 An example of the method to differentiate between rural and urban areas within a county.

Notes: Regions *a*-*h* represent towns in the county, and green and pink dots denote villages and urban communities, respectively. In this county, towns *e* and *f* are urban areas, while *a*, *b*, *c*, *d*, *g*, and *h* are rural towns.

Table C1 Impact of supermarket expansion on grain income

	Ln Sales revenue		Ln Production value		Ln Profit	
	(1)	(2)	(3)	(4)	(5)	(6)
Supermarkets	0.0047***	0.0080***	0.0043***	0.0055***	0.0064***	0.0080***
	(0.0017)	(0.0019)	(0.0014)	(0.0016)	(0.0017)	(0.0019)
Supermarkets×RUI	-0.0115***	-0.0214***	-0.0097***	-0.0133***	-0.0143***	-0.0186***
	(0.0038)	(0.0047)	(0.0031)	(0.0038)	(0.0043)	(0.0048)
Household head age		-0.0155		-0.0544		-0.0449
		(0.0630)		(0.0491)		(0.0594)
Household head age, squared		0.0003		0.0006		0.0005
		(0.0006)		(0.0005)		(0.0006)
Household head gender		0.0181		0.0353		0.0984
		(0.2455)		(0.2116)		(0.2417)
Household head marriage		0.3543*		0.4162***		0.4606**
		(0.1859)		(0.1440)		(0.1801)
Household head education		0.0057		0.0070		0.0288
		(0.0233)		(0.0195)		(0.0266)
Household size		0.0536		0.0091		0.0166
		(0.0519)		(0.0450)		(0.0665)
Number of children		0.0090		0.0153		0.0925
		(0.1014)		(0.0842)		(0.1179)
Number of elderly		-0.1529		-0.1224		-0.0665
		(0.1152)		(0.0931)		(0.1187)

Ln non-agricultural GDP		-0.2556		-0.0301		0.1341
		(0.2149)		(0.1774)		(0.2468)
Ln Population		-0.3212		0.1305		-0.0876
		(0.6310)		(0.4562)		(0.5198)
RUI	-0.3715	-11.6229**	-0.4141*	-11.0870***	-0.4937*	-13.6223***
	(0.2675)	(5.4101)	(0.2133)	(4.2300)	(0.2650)	(4.7756)
Household head age×RUI		0.2358		0.2808**		0.3332**
		(0.1730)		(0.1308)		(0.1580)
Household head age, squared×RUI		-0.0022		-0.0028**		-0.0033**
		(0.0016)		(0.0012)		(0.0015)
Household head gender×RUI		-0.1759		-0.3149		-0.4011
		(0.6723)		(0.5601)		(0.6432)
Household head marriage×RUI		-1.1575**		-1.2582***		-1.3402***
		(0.5329)		(0.3877)		(0.4624)
Household head education×RUI		0.0049		-0.0097		-0.0694
		(0.0688)		(0.0554)		(0.0799)
Household size×RUI		-0.0895		0.0543		0.0292
		(0.1444)		(0.1219)		(0.1728)
Number of children× RUI		0.0212		-0.0162		-0.1936
		(0.2907)		(0.2321)		(0.3066)
Number of elderly× RUI		0.3818		0.2449		0.1114
		(0.3329)		(0.2624)		(0.3177)
Ln Non-agricultural GDP×RUI		1.3648***		0.4630		0.5642
		(0.4684)		(0.3588)		(0.4284)

Ln Population×RUI		-0.3950		0.3510		0.5663
		(0.6802)		(0.5180)		(0.6051)
_cons	8.7299***	11.8078***	8.9249***	8.8699***	8.6536***	8.0883**
	(0.0906)	(4.1755)	(0.0724)	(3.1697)	(0.0906)	(3.9769)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,515	4,515	5,221	5,221	5,192	5,192
R-squared	0.7710	0.7754	0.7408	0.7444	0.6489	0.6538

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C2 Impact of supermarket expansion on grain income

	Ln Sales revenue		Ln Production value		Ln Profit	
	(1)	(2)	(3)	(4)	(5)	(6)
Supermarkets	-0.0003	-0.0001	-0.0000	0.0001	0.0001	0.0006
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Household head age		0.0729***		0.0480***		0.0786***
		(0.0225)		(0.0179)		(0.0225)
Household head age, squared		-0.0006***		-0.0004**		-0.0006***
		(0.0002)		(0.0002)		(0.0002)
Household head gender		-0.0167		-0.0581		-0.0170
		(0.1063)		(0.0751)		(0.0824)
Household head marriage		-0.0311		-0.0133		0.0003
		(0.0517)		(0.0429)		(0.0598)
Household head education		0.0080		0.0032		0.0050
		(0.0099)		(0.0073)		(0.0094)
Household size		0.0196		0.0262*		0.0235
		(0.0165)		(0.0137)		(0.0180)
Number of children		0.0204		0.0119		0.0326
		(0.0309)		(0.0246)		(0.0398)
Number of elderly		-0.0245		-0.0365		-0.0263
		(0.0343)		(0.0290)		(0.0412)
Ln Non-agricultural GDP		0.0917		0.0889		0.2801
		(0.1772)		(0.1540)		(0.2119)

Ln Population		-0.5915		0.1877		0.0314
		(0.5528)		(0.4133)		(0.4788)
_cons	8.6237***	9.2451**	8.8018***	5.5362*	8.5109***	3.9116
	(0.0129)	(3.7273)	(0.0119)	(2.8506)	(0.0143)	(3.6712)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,515	4,515	5,221	5,221	5,192	5,192
R-squared	0.7687	0.7706	0.7384	0.7401	0.6452	0.6477

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C3 Impact of supermarket expansion on production value per unit land area

	Ln Production value per mu	
	(1)	(2)
Supermarkets	0.0031**	0.0037***
	(0.0012)	(0.0013)
Supermarkets×RUI	-0.0078**	-0.0094***
	(0.0030)	(0.0031)
Household head age	-0.0304	-0.0406
	(0.0429)	(0.0418)
Household head age, squared	0.0004	0.0005
	(0.0004)	(0.0004)
Household head gender	0.0184	0.0299
	(0.1906)	(0.1808)
Household head marriage	0.1453	0.2313*
	(0.1263)	(0.1206)
Household head education	0.0110	0.0098
	(0.0165)	(0.0158)
Household size	-0.0451	-0.0256
	(0.0359)	(0.0355)
Number of children	0.0294	0.0292
	(0.0816)	(0.0762)
Number of elderly	0.0394	-0.0037
	(0.0822)	(0.0794)

Ln Non-agricultural GDP	-0.1008	-0.1071
	(0.1617)	(0.1521)
Ln Population	0.0576	0.0643
	(0.4828)	(0.4180)
RUI	-7.6159**	-8.9330**
	(3.5050)	(3.5063)
Household head age×RUI	0.1776	0.2154*
	(0.1130)	(0.1103)
Household head age, squared×RUI	-0.0017	-0.0021**
	(0.0011)	(0.0010)
Household head gender×RUI	-0.2250	-0.2755
	(0.5168)	(0.4780)
Household head marriage×RUI	-0.4813	-0.7247**
	(0.3569)	(0.3318)
Household head education×RUI	-0.0384	-0.0286
	(0.0491)	(0.0462)
Household size×RUI	0.1269	0.0988
	(0.0992)	(0.0971)
Number of children×RUI	-0.1048	-0.0890
	(0.2360)	(0.2170)
Number of elderly×RUI	-0.1392	-0.0471
	(0.2351)	(0.2253)
Ln Non-agricultural GDP×RUI	0.7761**	0.6717**
	(0.3248)	(0.3033)

Ln Population×RUI	-0.2025	-0.0108
	(0.4425)	(0.4275)
Ln Land area		-0.4260***
		(0.0755)
Ln Land area×RUI		0.0130
		(0.1984)
_cons	8.0542**	8.9546***
	(3.2121)	(2.8668)
Household FE	Yes	Yes
Year FE	Yes	Yes
Province-by-year FE	Yes	Yes
N	5,221	5,221
R-squared	0.5418	0.5802

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C4 Robustness checks on the impact of supermarket expansion on production value per unit land area

	Ln Production value per mu			
	(1) Rice-producing provinces	(2) Wheat-producing provinces	(3) Corn-producing provinces	(4) Smallholder farmers
Supermarkets	0.0040***	0.0033**	0.0037***	0.0037***
	(0.0013)	(0.0014)	(0.0013)	(0.0013)
Supermarkets×RUI	-0.0103***	-0.0082**	-0.0097***	-0.0092***
	(0.0032)	(0.0034)	(0.0030)	(0.0031)
Household head age	-0.0406	-0.0533	-0.0372	-0.0474
	(0.0446)	(0.0565)	(0.0421)	(0.0428)
Household head age, squared	0.0005	0.0006	0.0004	0.0005
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Household head gender	0.1570	0.1216	0.0451	0.0307
	(0.1935)	(0.2317)	(0.1852)	(0.1813)
Household head marriage	0.2843**	0.3091**	0.2644**	0.2633**
	(0.1292)	(0.1436)	(0.1203)	(0.1228)
Household head education	0.0092	0.0251	0.0128	0.0115
	(0.0199)	(0.0178)	(0.0160)	(0.0159)
Household size	-0.0284	-0.0382	-0.0369	-0.0260
	(0.0403)	(0.0433)	(0.0360)	(0.0361)
Number of children	0.0061	0.1001	0.0667	0.0269
	(0.0834)	(0.0922)	(0.0778)	(0.0767)
Number of elderly	0.0991	-0.0597	0.0124	-0.0173
	(0.0869)	(0.0988)	(0.0791)	(0.0808)

Ln Non-agricultural GDP	-0.1816	0.3867*	-0.0868	-0.0560
	(0.1647)	(0.2311)	(0.1521)	(0.1553)
Ln Population	-0.0357	0.5030	0.0374	0.1156
	(0.4562)	(0.4502)	(0.4218)	(0.4157)
RUI	-8.9024**	-9.6232**	-9.3571***	-8.7757**
	(3.8024)	(4.4807)	(3.5376)	(3.5689)
Household head age×RUI	0.2090*	0.2747*	0.2176*	0.2241**
	(0.1177)	(0.1408)	(0.1112)	(0.1116)
Household head age, squared×RUI	-0.0020*	-0.0027**	-0.0021**	-0.0022**
	(0.0011)	(0.0013)	(0.0011)	(0.0011)
Household head gender×RUI	-0.6396	-0.4694	-0.3013	-0.2840
	(0.4979)	(0.5823)	(0.4911)	(0.4785)
Household head marriage×RUI	-0.8538**	-0.9501**	-0.8011**	-0.7821**
	(0.3556)	(0.3839)	(0.3321)	(0.3348)
Household head education×RUI	-0.0268	-0.0686	-0.0319	-0.0305
	(0.0546)	(0.0513)	(0.0470)	(0.0467)
Household size×RUI	0.0889	0.1371	0.1280	0.1078
	(0.1082)	(0.1163)	(0.0979)	(0.0985)
Number of children×RUI	-0.0109	-0.2125	-0.1716	-0.0758
	(0.2378)	(0.2545)	(0.2202)	(0.2175)
Number of elderly×RUI	-0.3349	0.1440	-0.1077	-0.0197
	(0.2454)	(0.2723)	(0.2245)	(0.2281)
Ln Non-agricultural GDP×RUI	0.8418***	0.6431*	0.6412**	0.7064**
	(0.3245)	(0.3897)	(0.3038)	(0.3056)

Ln Population×RUI	-0.1054	0.1023	0.1208	-0.1144
	(0.4515)	(0.5675)	(0.4309)	(0.4329)
Ln Land area	-0.4389***	-0.3728***	-0.4011***	-0.4639***
	(0.0800)	(0.1145)	(0.0761)	(0.0873)
Ln Land area×RUI	0.0431	-0.2958	-0.0247	-0.0249
	(0.2084)	(0.2839)	(0.2003)	(0.2226)
_cons	9.8918***	2.5562	8.7477***	8.4948***
	(3.1571)	(3.3964)	(2.8736)	(2.8787)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
N	4,070	3,102	4,915	5,036
R-squared	0.5931	0.4841	0.5865	0.5623

Notes: Rice-producing provinces include Liaoning, Heilongjiang, Jiangsu, Hubei, Hunan, Guangxi, Guizhou, and Chongqing. Wheat-producing provinces include Jiangsu, Shandong, Henan, Hubei, Guizhou, and Chongqing. Corn-producing provinces include Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Guangxi, Guizhou, and Chongqing. Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table C5 Impact of supermarket expansion on the farm-gate grain price using CFPS data

	Ln Farm-gate grain price			
	(1)	(2)	(3)	(4)
Supermarkets	0.0026***	0.0015*	0.0025***	0.0019**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Supermarkets×RUI	-0.0063***	-0.0037*	-0.0058***	-0.0045**
	(0.0023)	(0.0021)	(0.0022)	(0.0022)
Household head age	0.0000	0.0013	-0.0002	0.0018
	(0.0058)	(0.0057)	(0.0057)	(0.0056)
Household head age, squared	0.0000	-0.0000	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Household head gender	0.0022	0.0001	0.0014	0.0114
	(0.0179)	(0.0173)	(0.0177)	(0.0180)
Household head marriage	0.0029	0.0039	0.0039	0.0018
	(0.0099)	(0.0098)	(0.0098)	(0.0101)
Household head education	-0.0030	-0.0026	-0.0028	-0.0030
	(0.0021)	(0.0020)	(0.0020)	(0.0020)
Household size	-0.0061	-0.0038	-0.0051	0.0008
	(0.0057)	(0.0056)	(0.0056)	(0.0058)
Number of children	0.0148	0.0151	0.0146	0.0069
	(0.0110)	(0.0109)	(0.0110)	(0.0110)
Number of elderly	-0.0093	-0.0077	-0.0106	-0.0084
	(0.0127)	(0.0122)	(0.0125)	(0.0123)

Ln Non-agricultural GDP	-0.0171	-0.0122	-0.0161	-0.0088
	(0.0169)	(0.0165)	(0.0168)	(0.0168)
Ln Population	-0.0100	-0.0157	-0.0111	-0.0214
	(0.0263)	(0.0261)	(0.0261)	(0.0266)
RUI	-0.0040	0.0398	-0.0265	-0.2433
	(0.4470)	(0.4446)	(0.4447)	(0.4528)
Household head age×RUI	-0.0004	-0.0033	0.0001	-0.0051
	(0.0149)	(0.0147)	(0.0148)	(0.0145)
Household head age, squared×RUI	-0.0000	0.0000	-0.0000	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Household head gender×RUI	-0.0129	-0.0068	-0.0108	-0.0353
	(0.0452)	(0.0436)	(0.0446)	(0.0455)
Household head marriage×RUI	-0.0118	-0.0158	-0.0139	-0.0085
	(0.0254)	(0.0253)	(0.0251)	(0.0259)
Household head education×RUI	0.0093^{*}	0.0085^{*}	0.0091^{*}	0.0095^{*}
	(0.0052)	(0.0050)	(0.0051)	(0.0052)
Household size×RUI	0.0129	0.0072	0.0105	-0.0038
	(0.0144)	(0.0143)	(0.0143)	(0.0146)
Number of children×RUI	-0.0229	-0.0243	-0.0219	-0.0031
	(0.0280)	(0.0277)	(0.0278)	(0.0280)
Number of elderly×RUI	0.0250	0.0217	0.0279	0.0216
	(0.0314)	(0.0302)	(0.0309)	(0.0306)
Ln Non-agricultural GDP×RUI	0.1086^{***}	0.0991^{**}	0.1054^{***}	0.0835^{**}
	(0.0411)	(0.0401)	(0.0407)	(0.0408)

Ln Population×RUI	-0.1114*	-0.0941	-0.1047	-0.0725
	(0.0652)	(0.0648)	(0.0648)	(0.0662)
Ln Land area				-0.0598***
				(0.0118)
Ln Land area×RUI				0.1479***
				(0.0305)
_cons	5.1396***	5.1091***	4.9176***	5.0020***
	(0.1749)	(0.1727)	(0.1737)	(0.1757)
Province FE	Yes	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-by-year FE	No	Yes	No	No
Crop-by-year FE	No	No	Yes	Yes
N	5,230	5,230	5,230	5,230
R-squared	0.4604	0.4779	0.4710	0.4749

Notes: Each column reports coefficients from a fixed-effects regression using the CFPS sample. Standard errors (in parentheses) are clustered at the household level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C6 Impact of supermarket expansion on farmers' commercialization

	Commercialization rate		
	(1)	(2)	(3)
Supermarkets	0.0273	0.1772***	0.1497***
	(0.0170)	(0.0555)	(0.0551)
Supermarkets×RUI		-0.4311***	-0.3664***
		(0.1396)	(0.1375)
Household head age	0.7452	2.5089	2.7373*
	(0.6532)	(1.6239)	(1.6078)
Household head age, squared	-0.0064	-0.0256*	-0.0281*
	(0.0057)	(0.0147)	(0.0146)
Household head gender	1.3971	-11.8683	-12.4362
	(3.1440)	(9.0638)	(9.1041)
Household head marriage	-1.8771	-8.5145	-10.8758**
	(1.5401)	(5.4062)	(5.3139)
Household head education	-0.0304	-1.1852*	-1.1275*
	(0.2631)	(0.6689)	(0.6506)
Household size	-0.3129	2.6926*	2.1722
	(0.4604)	(1.4166)	(1.3725)
Number of children	-0.6520	-2.5091	-2.7246
	(0.8224)	(2.8712)	(2.8190)
Number of elderly	0.5331	-3.2023	-2.0616
	(1.0097)	(3.2744)	(3.2018)
Ln Non-agricultural GDP	-2.8209	-8.2472	-6.8173

	(4.9145)	(6.5010)	(6.4330)
Ln Population	-42.4896**	-51.3963***	-53.9843***
	(16.9823)	(18.5389)	(18.8957)
RUI	-42.0974***	-245.9257*	-282.4076*
	(7.5929)	(142.5518)	(146.2524)
Household head age×RUI		-4.7619	-5.7005
		(4.1984)	(4.0946)
Household head age, squared×RUI		0.0530	0.0624*
		(0.0384)	(0.0373)
Household head gender×RUI		37.8630	40.0185
		(24.2666)	(24.9032)
Household head marriage×RUI		20.1746	26.8852*
		(16.1206)	(15.7735)
Household head education×RUI		3.4940*	3.1210*
		(1.9295)	(1.8732)
Household size×RUI		-8.3632**	-7.7286**
		(3.9195)	(3.8200)
Number of children×RUI		5.1215	5.3948
		(8.0854)	(7.9252)
Number of elderly×RUI		10.9486	8.3871
		(8.9347)	(8.7261)
Ln Non-agricultural GDP×RUI		26.5254*	27.1750**
		(14.0266)	(13.4911)
Ln Population×RUI		13.0762	16.4380

		(19.5847)	(19.4824)
Ln Land area			6.8399**
			(2.8908)
Ln Land area×RUI			17.9540**
			(7.9996)
_cons	337.9755***	404.6134***	396.6671***
	(113.5914)	(122.6408)	(125.0907)
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes
N	5,221	5,221	5,221
R-squared	0.6752	0.6797	0.6956

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C7 Impact of supermarket expansion on farmers' resource allocation

	Ln Land area	Ln Grain production hours	Ln Purchased input cost
	(1)	(2)	(3)
c	0.0015**	0.0074***	0.0067***
	(0.0007)	(0.0025)	(0.0019)
Supermarkets×RUI	-0.0037**	-0.0257***	-0.0127***
	(0.0018)	(0.0065)	(0.0047)
Household head age	-0.0242	-0.2119*	-0.0340
	(0.0290)	(0.1120)	(0.0898)
Household head age, squared	0.0002	0.0020**	0.0004
	(0.0003)	(0.0010)	(0.0008)
Household head gender	0.0275	0.2562	-0.5846
	(0.1287)	(0.4367)	(0.5129)
Household head marriage	0.2036**	0.4639	0.4278
	(0.0932)	(0.3233)	(0.3154)
Household head education	-0.0030	0.0515	-0.0626*
	(0.0123)	(0.0549)	(0.0324)
Household size	0.0460*	-0.0891	0.0339
	(0.0247)	(0.1129)	(0.0748)
Number of children	-0.0002	0.1821	0.1178
	(0.0508)	(0.2146)	(0.1423)
Number of elderly	-0.1019*	-0.0987	-0.1400
	(0.0526)	(0.2435)	(0.1571)

Ln Non-agricultural GDP	-0.0171	-1.3232***	0.3042
	(0.1190)	(0.4407)	(0.3033)
Ln Population	0.0200	-1.2180	-1.3424*
	(0.3425)	(0.8935)	(0.7961)
RUI	-2.9945	-22.0378**	-9.2693
	(2.7424)	(9.9082)	(7.1831)
Household head age×RUI	0.0892	0.4503	-0.0298
	(0.0768)	(0.2918)	(0.2308)
Household head age, squared×RUI	-0.0008	-0.0046*	0.0002
	(0.0007)	(0.0026)	(0.0021)
Household head gender×RUI	-0.1206	-0.1992	1.4675
	(0.3701)	(1.0938)	(1.3383)
Household head marriage×RUI	-0.5760**	-1.3078	-0.5821
	(0.2668)	(0.9021)	(0.8664)
Household head education×RUI	0.0232	-0.0197	0.1895**
	(0.0353)	(0.1443)	(0.0906)
Household size×RUI	-0.0662	0.3061	0.0300
	(0.0667)	(0.3066)	(0.2005)
Number of children×RUI	0.0362	-0.2916	-0.3620
	(0.1440)	(0.5728)	(0.3906)
Number of elderly×RUI	0.2179	0.0148	0.4496
	(0.1477)	(0.6563)	(0.4324)
Ln Non-agricultural GDP×RUI	-0.2433	2.4289***	0.1797
	(0.2341)	(0.8235)	(0.5240)

Ln Population×RUI	0.4391	-0.4717	1.2575
	(0.3421)	(1.2416)	(0.9206)
_cons	2.1026	27.5856***	13.7363**
	(2.2679)	(6.3286)	(5.5982)
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes
N	5,221	5,221	5,221
R-squared	0.8622	0.5013	0.5772

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C8 Impact of supermarkets on off-farm work and non-grain agricultural production

	Participation in off-farm work (dummy)	Ln Income from off-farm work	Engaging in non-grain agricultural production (dummy)	Income from selling non-grain agricultural products
	(1)	(2)	(3)	(4)
Supermarkets	-0.0012	-0.0099**	-0.0005	-0.0014
	(0.0009)	(0.0040)	(0.0005)	(0.0031)
Supermarkets×RUI	0.0035*	0.0254**	0.0007	-0.0014
	(0.0020)	(0.0099)	(0.0013)	(0.0081)
Household head age	-0.0402	0.1022	-0.0200	0.2591
	(0.0327)	(0.1306)	(0.0220)	(0.1824)
Household head age, squared	0.0004	-0.0003	0.0002	-0.0021
	(0.0003)	(0.0012)	(0.0002)	(0.0016)
Household head gender	0.0706	-0.8573	0.0724	-0.8005
	(0.1677)	(0.6922)	(0.0907)	(0.6838)
Household head marriage	0.3189***	1.4304***	-0.0430	0.6154
	(0.1137)	(0.4950)	(0.0778)	(0.5775)
Household head education	0.0310**	-0.0497	-0.0180*	0.0086
	(0.0133)	(0.0698)	(0.0098)	(0.0531)
Household size	-0.0049	0.1606	0.0010	-0.0342
	(0.0330)	(0.1520)	(0.0195)	(0.1240)
Number of children	0.0127	-0.3138	0.0025	-0.2919
	(0.0579)	(0.2556)	(0.0365)	(0.2501)
Number of elderly	-0.0206	0.0450	-0.0069	0.0312
	(0.0740)	(0.3189)	(0.0455)	(0.2720)

Ln Non-agricultural GDP	0.2302*	0.3941	-0.0524	0.5540
	(0.1297)	(0.5426)	(0.0935)	(0.8122)
Ln Population	0.5593	-1.7167	-0.0302	1.4281
	(0.3549)	(1.4244)	(0.1856)	(1.3110)
RUI	-1.7773	-1.7961	-2.4138	12.6166
	(2.7100)	(10.6878)	(1.8300)	(14.7113)
Household head age×RUI	0.1434*	-0.0311	0.0909	-0.5639
	(0.0839)	(0.3139)	(0.0554)	(0.4396)
Household head age, squared×RUI	-0.0013	-0.0011	-0.0008	0.0042
	(0.0008)	(0.0029)	(0.0005)	(0.0040)
Household head gender×RUI	-0.1283	2.6689*	-0.1163	3.2751*
	(0.4236)	(1.5436)	(0.2474)	(1.8726)
Household head marriage×RUI	-0.2575	-2.5640**	0.1047	-2.2087
	(0.3254)	(1.3011)	(0.2229)	(1.6652)
Household head education×RUI	-0.0695*	0.1785	0.0376	0.0801
	(0.0375)	(0.1777)	(0.0256)	(0.1358)
Household size×RUI	0.0776	0.0328	-0.0201	0.0460
	(0.0886)	(0.3956)	(0.0537)	(0.3376)
Number of children×RUI	0.0293	0.8969	0.0613	0.8576
	(0.1642)	(0.7026)	(0.1033)	(0.6794)
Number of elderly×RUI	0.0464	-0.5689	0.0088	0.2565
	(0.1977)	(0.7935)	(0.1235)	(0.7478)
Ln Non-agricultural GDP×RUI	-0.2460	-0.2783	0.1305	0.9540
	(0.2527)	(1.0356)	(0.1579)	(1.2093)

Ln Population×RUI	-0.1021	0.8604	-0.1554	-0.6775
	(0.3474)	(1.6023)	(0.2170)	(1.8417)
_cons	-3.7319	12.4120	1.9235	-11.7302
	(2.4710)	(9.9081)	(1.4686)	(10.8319)
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Province-by-year FE	Yes	Yes	Yes	Yes
N	5,221	2,751	5,221	1,842
R-squared	0.5043	0.6415	0.6106	0.6923

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C9 Impact of supermarkets on household gross income

	Ln Household gross income	
	(1)	(2)
Supermarkets	0.0009*	0.0003
	(0.0005)	(0.0015)
Supermarkets×RUI		0.0012
		(0.0037)
Household head age	0.0529**	0.0510
	(0.0212)	(0.0529)
Household head age, squared	-0.0004**	-0.0002
	(0.0002)	(0.0005)
Household head gender	0.0501	-0.3219
	(0.1025)	(0.2623)
Household head marriage	0.2337***	0.3283*
	(0.0533)	(0.1858)
Household head education	0.0096	0.0207
	(0.0087)	(0.0231)
Household size	0.0953***	0.0614
	(0.0160)	(0.0523)
Number of children	0.0383	-0.0895
	(0.0276)	(0.0999)
Number of elderly	-0.0368	-0.1082
	(0.0346)	(0.1199)

Ln Non-agricultural GDP	0.0743	-0.1562
	(0.1767)	(0.2174)
Ln Population	-0.2960	-0.1254
	(0.5017)	(0.5444)
RUI	0.0829	-1.4173
	(0.2177)	(4.4039)
Household head age×RUI		0.0045
		(0.1396)
Household head age, squared×RUI		-0.0005
		(0.0013)
Household head gender×RUI		1.0345
		(0.6503)
Household head marriage×RUI		-0.2905
		(0.5219)
Household head education×RUI		-0.0349
		(0.0627)
Household size×RUI		0.1011
		(0.1509)
Number of children×RUI		0.3917
		(0.2922)
Number of elderly×RUI		0.1974
		(0.3330)
Ln Non-agricultural GDP×RUI		0.8620**
		(0.4329)

Ln Population×RUI		-0.7393
		(0.5942)
_cons	9.2818***	9.8596***
	(3.4719)	(3.8150)
Household FE		
Year FE		
Province-by-year FE		
N	5,221	5,221
R-squared	0.6084	0.6111

Notes: Each column reports coefficients from a fixed-effects regression using the CHNS sample. Standard errors (in parentheses) are clustered at the household level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.