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Shocks, Market Pass-Through and Paddy Producers' Food Security: Evidence from Sri Lanka

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Abstract

This paper examines how local price transmission dynamics shape the welfare effects of food price shocks. We study Sri Lanka's 2022 economic crisis, a compound shock that disrupted rice production, supply chains, and food prices, using a panel of paddy-producing households matched with weekly market-level rice prices. The analysis links two literatures that are usually treated separately: studies of food-price shocks and household welfare, and studies of market integration and price transmission. We estimate a household fixed-effects instrumental-variable model in which retail rice prices are instrumented by the interaction between shock-induced changes in district-level wholesale–retail price-transmission speed, measured by the error-correction term, and predetermined distance from economic centres. The results show that shock-transmitted increases in retail rice prices significantly reduce household food security: a one-rupee increase in retail rice prices lowers the Food Consumption Score by 1.16 points on average. Heterogeneity analyses support the proposed mechanism. The negative effect is concentrated among highly commercialized paddy-producing households, while effects for non-selling and low-selling households are consistently smaller and statistically insignificant. Food-security losses are also concentrated in districts where wholesale–retail pass-through shifted from symmetric to asymmetric adjustment. These findings suggest that market participation may increase vulnerability when retail price increases are not matched by proportional or timely gains at the farmgate level. The paper shows that food-price surges may trigger food insecurity not only through price levels, but also through the way exogenous shocks are transmitted along local value chains.

Keywords: food price spikes, asymmetric price transmission, food security, rice producers, Sri Lanka.

JEL: E31, D43, Q18, Q12, O53.

1. Introduction

Over the last decades, food price shocks have increased in both international and national markets (Zseleczky & Yosef, 2014; Cottrell et al., 2019),[1] threatening food security, particularly in developing countries (Headey & Martin, 2016; Amolegbe et al., 2021; Hassen & El Bilali, 2022; Alam et al., 2024; Dhar et al., 2024; Onumah et al., 2024). The interplay of multiple risks, including climate change-related shocks, macroeconomic volatility, restrictive trade policies, public health crises, and geopolitical tensions, has intensified this challenge. Each shock, per se, can disrupt the agrifood systems. However, when shocks are compounded, their effects can be larger than the sum of their individual impacts due to nonlinear interactions and cascading effects across the agrifood system, with far-reaching consequences for both producers and consumers (Ansah et al., 2021; Rakoto Harison et al., 2024).

Rising food prices erode the purchasing power of net food buyers, especially poorer farming households who allocate a large share of their income to food, thus exacerbating their vulnerability to food insecurity. At the same time, net food sellers may benefit from improved agricultural revenues, although this effect depends on the extent to which they are engaged in market transactions, market efficiency, and broader trade dynamics. Subsistence producers may be insulated from price fluctuations due to limited participation in food markets, whereas more market-integrated producers can potentially gain or lose from price surges (Dorward, 2012; Headey & Martin, 2016; Laborde et al., 2021b).

Empirical evidence, particularly from the 2007–2008 global food price crisis, focuses largely on the welfare consequences of food price inflation, with mixed findings depending on whether households are net buyers or net sellers, whether effects are measured in the short or longer run, and whether agricultural supply and wage responses are considered (Ivanic & Martin, 2008; Verpoorten et al., 2013b; Headey & Martin, 2016; Headey, 2018). Most studies report worsened food insecurity among urban and poor households (Ruel et al., 2010), reflected in reduced consumption, poorer dietary diversity, and reliance on adverse coping mechanisms (Brinkman et al., 2010; Compton et al., 2010; Gonzalez Davila, 2010; Akter & Basher, 2014; D'Souza & Jolliffe, 2012; Prevel et al., 2012). Other research highlights improved livelihoods for net producers who benefitted from higher prices (Dorward, 2012; Headey, 2018; Headey & Hirvonen, 2023; Sehgal, 2024).

Less attention has been devoted to how price transmission structures shape these impacts. Yet food price spikes reach households through imperfectly integrated markets, and their welfare effects depend not only on the magnitude of international or wholesale price changes, but also on spatial market integration, transaction and transport costs, vertical price transmission, and the speed/asymmetry of adjustment

[1] After the food price crisis of 2007-08, the average level and the volatility of these prices has never returned to pre-crisis levels, with recurrent spikes as in 2010-11, that marked other global food price surges such as that of 2016, due to El Niño-induced supply shocks, and that of 2022, in the aftermath of the COVID-19 pandemic and of the Russian invasion of Ukraine.

along the supply chain (Goodwin & Piggott, 2001; Meyer & von Cramon-Taubadel, 2004; Gedara Korale et al., 2015; Ceballos et al., 2017; Chou & Lin, 2019; von Cramon-Taubadel & Goodwin, 2021).

This paper contributes to the literature on food price spikes and household food security by examining how the speed of price transmission mediates the pass-through of an exogenous shock to household food security. We identify these mechanisms through an instrumental variable approach and a unique nationwide panel dataset collected in Sri Lanka by FAO between 2022 and 2023. In particular, granular rice prices at the retail market are instrumented using the interaction between district-level variation of the speed of price transmission in the aftermath of an exogenous shock, measured by changes in the wholesale–retail error correction term relative to the pre-shock period, and farmer-level distance to the nearest economic centre measured at baseline.

In doing this, our analysis bridges two strands of literature: one examining how food price spikes affect household food security, typically taking observed prices as given without modelling the transmission process that generates them (Ruel et al., 2010; Ivanic & Martin, 2014; Headey & Martin, 2016; Laborde et al., 2021a); and one studying how shocks propagate along supply chains, without tracing how heterogeneity in pass-through may translate into differential welfare outcomes (Meyer & von Cramon-Taubadel 2004; von Cramon-Taubadel & Goodwin, 2021).

We chose Sri Lanka as a case study because the country experienced during 2021 and 2022 several compound shocks, which are related but different in nature. These shocks eventually turned into the most severe economic crisis in the country's recent history. Such an unfortunate conjuncture determined a unique empirical context for examining the pass-through from food price spikes to producer households' food security in the aftermath of an exogenous shock. Starting from April 2021, a ban on chemical fertilizer imports, implemented overnight to allegedly promote organic farming and save foreign reserves, backfired due to insufficiently available organic fertilizer alternatives. Although the ban was lifted after widespread protests in November 2021 (Weerahewa & Dayananda, 2023) rice yields during the 2021/2022 *Maha*[2] season fell by 34%, from an average of 4.6–4.9 million metric tons to 3.39 million metric tons. The consequent food price surge was additionally fuelled by global supply chain disruptions linked to COVID-19 and subsequently to the war in Ukraine, which destabilized food and energy markets worldwide (Hassen & El Bilali, 2022), generating fertilizer price rise on global markets (Hebebrand & Laborde, 2023), which severely limited their use in agricultural production. As a consequence, from September 2022, food inflation peaked at a historic 94.9% per year, reaching its maximum with the country ranking sixth globally by November (Central Bank of Sri Lanka, 2022; World Bank, 2022). By October 2022, an estimated 6.3 million people, or

[2] *Maha* (October – March) is the primary agricultural growing season in Sri Lanka, while *Yala* (April – September) is the secondary growing season.

30% of the Sri Lankan population, faced acute food insecurity (FAO & WFP, 2023) due to the pivotal role of rice production in Sri Lanka's economy and diet.[3]

The results from our analysis show that retail rice price inflation is one of the channels through which the shock propagates into household food security losses, with a one-Rupee increase in retail rice prices reducing the Food Consumption Score by 1.16 points on average. This effect is mainly driven by market-integrated producer households, for whom incomplete farmgate price adjustment compounds the consumption cost of rising staple prices. Heterogeneity across districts with asymmetric pass-through further corroborates the proposed transmission mechanism, providing supporting evidence for the causal interpretation of the results.

The remainder of the paper is organized as follows. Section 2 reviews the literature, Section 3 provides the conceptual framework underlying our analysis, Section 4 presents the data and the empirical strategy, Section 5 discusses the results, and Section 6 concludes.

2. Literature review

This section reviews two strands of literature that this paper aims to bring into dialogue. The first examines the welfare impact of food price shocks on household food security. A large body of work in this tradition identifies the sign and magnitude of welfare effects by exploiting variation in households' market position, distinguishing between net buyers, who are harmed by price increases, and net sellers, who may benefit. More recent contributions have refined this framework by incorporating livelihood heterogeneity, subsistence constraints, and dynamic behavioural responses. Nonetheless, this literature consistently takes observed prices as given, treating the transmission mechanism as a black box, meaning that the mechanisms by which price movements are filtered through supply chains and market transmission before reaching households are not explicitly modelled. Nonetheless, most of the empirical literature remains constrained by identification challenges. Many studies rely on cross-sectional data and observational correlations, raising concerns about endogeneity and limiting causal interpretation. As noted by Alam et al. (2024), there is a need for studies employing panel data and credible identification strategies capable of isolating the causal effects of food price spikes on household welfare.

The second strand of literature focuses precisely on the price transmission mechanisms. Drawing on spatial price analysis, cointegration methods, and error-correction models, this literature documents how price shocks propagate along supply chains and across spatially integrated markets, and identifies the structural and institutional factors, including transaction costs, market power, infrastructure, and trade policy, that govern the speed, the completeness, and the symmetry of the pass-through. A well-established finding in this literature is that pass-through is often

[3] In fact, rice accounts for 34% of cultivated land, directly or indirectly employing nearly 30% of the workforce sourcing livelihood for about 1.8 million farming households (FAO & WFP, 2023). It is also the main staple food of the Sri Lankan population, with an average annual per capita consumption of 100 kg, contributing 42% of daily caloric intake and 34% of protein intake (Central Bank of Sri Lanka, 2020).

incomplete and asymmetric, with prices adjusting more rapidly to increases than to decreases. Yet despite its rich characterization of transmission dynamics, this literature rarely traces how heterogeneity in pass-through translates into differential impacts of price inflation on household welfare outcomes, leaving the distributional implications of imperfect transmission largely unexplored[4].

2.1. Empirical Evidence on Food Price Shocks and Food Security

A large empirical literature examines how food price surges affect household welfare, food security, and nutrition. This evidence is best read along three interrelated dimensions. First, the origin of food price spikes matters. The 2007-2008 literature focused on international staple-price spikes amplified by energy prices, low stocks, biofuel demand, financial turbulence, and trade-policy responses; more recent episodes combine food-price inflation with exogenous shocks such as COVID-19 disruptions, the Russia-Ukraine war, energy and fertilizer shocks, domestic macroeconomic instability, and escalating climate volatility. Second, household transmission channels matter: price surges affect welfare through purchasing power, own-production income, wage and factor-market responses, dietary substitution, coping strategies, and local price pass-through. Third, the level of analysis matters because global models, country studies, and subnational evidence capture different parts of the transmission process, from aggregate exposure to the prices households face. The discussion below is organized accordingly.

2.1.1. Food price inflation origin

The benchmark evidence comes from the 2007-2008 and 2010-2011 food price surges, when large increases in international staple prices generated concern about poverty, hunger, and social instability. The origins of these spikes were primarily global and market-based: rising energy prices, low grain stocks, biofuel demand, financial turbulence, exchange-rate movements, and trade-policy responses contributed to higher international food prices and greater volatility (Headey & Fan, 2010; Headey, 2011; Headey & Martin, 2016). Studies of this period generally ask how international price increases affected household real income, poverty, consumption, and nutrition once transmitted to domestic markets.

More recent inflationary episodes differ in origin and composition. Global covariate shocks such as COVID-19 pandemic and the Russia-Ukraine war compounded with domestic macroeconomic instability, fertilizer and energy shortages, and climate-related production risks may create the conditions for which food-price inflation interacts with income losses, logistics disruptions, input-price increases, trade restrictions, and employment shocks. Laborde et al. (2021b) show that pandemic-

[4] A small body of research brings these perspectives together by examining how international or national food price shocks are transmitted to domestic markets before assessing their welfare implications (Minot, 2011; Cudjoe et al., 2010; Rahman et al., 2022). In these studies, price transmission is typically estimated to characterize the extent to which external shocks are passed through to domestic prices, while welfare effects are subsequently inferred through simulations, consumer surplus calculations, or poverty analyses, rather than being estimated from observed household welfare outcomes. By contrast, this paper examines changes in local price-transmission dynamics within the domestic Sri Lanka's rice value chain to identify their causal effect on observed household food security.

related income losses and supply-chain disruptions jointly worsened poverty, food insecurity, and diet quality. Household-level studies point in the same direction. Hirvonen et al. (2021) document changes in food consumption and food security in urban Ethiopia during the pandemic, while Kansiime et al. (2021) find that food security and dietary quality worsened in Kenya and Uganda, particularly among income-poor and labour-dependent households. Amolegbe et al. (2021), using nationally representative panel data from Nigeria, show that unexpected increases in the prices of staples such as maize, rice, and cassava reduced household food access and availability. Alam et al. (2024), using high-frequency panel data from Burkina Faso, find that food price surges during the COVID period produced persistent increases in moderate and severe food insecurity, especially among poorer and rural households. In Benin, Nonvide et al. (2025) find that rising food prices weakened household resilience, increased indebtedness, and raised reliance on informal support.

These studies suggest that recent food-price inflation is not simply repetitions of 2007-2008: it is related to global covariate exogenous shocks that compound with other shocks at national or local level which may involve disruptions to production, trade, income, input markets, and local market functioning. Their welfare effects therefore depend not only on the size of the observed price increase, but also on whether the initial shock is environmental, economic, health-related, conflict-related, or macroeconomic, and on how these origins combine. This is directly relevant for Sri Lanka's 2022 crisis during which global supply-chain disruptions, the Russia-Ukraine war, fertilizer shortages, macroeconomic instability, and domestic production constraints overlapped.

2.1.2. Household transmission channels

Food price shocks affect household welfare through mutually reinforcing mechanisms that translate market-price changes into food access, diet quality and nutritional outcomes. In agrarian economies, households are not only consumers: many are also producers, wage workers, borrowers and participants in thin local markets. The welfare effect of a price increase therefore depends on how it changes real purchasing power, farm and non-farm income, input costs, coping behaviour and the terms on which households buy and sell food. This perspective is rooted in agricultural household models, where production and consumption are jointly determined under missing or imperfect markets (Singh et al., 1986; de Janvry et al., 1991).

The most immediate channel is real purchasing power. For net food buyers, higher staple prices raise the cost of a consumption bundle and reduce real income. The net benefit ratio captures this mechanism by comparing household net commodity sales with expenditure on that commodity (Deaton, 1989; Budd, 1993; Barrett & Dorosh, 1996; Ivanic & Martin, 2008). In the short run, when production, wages and household composition cannot adjust, this effect is often negative for poor rural households, including smallholders who sell after harvest but later return to the market as consumers. This mechanism is therefore central for Sri Lankan paddy producers, for whom higher retail rice prices may reduce welfare even when the household is involved in rice production.

At the same time, the consumer-price effect is mediated by income and factor-market responses. Higher food prices may increase revenues for net sellers, stimulate demand for agricultural labour, or raise rural wages, thereby offsetting part of the consumption loss. Ravallion (1990) shows that wage responses can change the distributional effects of food price increases, and Jacoby (2016) finds that rural wage adjustment may turn higher agricultural prices into gains for some households. Yet these benefits depend on whether higher retail or wholesale prices are transmitted to farm-gate prices, on households' ability to market output, and on whether food inflation coincides with higher fuel, fertilizer, credit and transport costs. Imperfect credit and output markets can also affect the timing of sales and purchases, limiting producers' ability to benefit from favourable prices (Stephens & Barrett, 2011).

When prices rise faster than income, households adjust diets and intertemporal choices. They may reduce dietary diversity, replace nutrient-rich foods with cheaper calories, or cut quantities, protecting calories in the short run while worsening nutrition. In Afghanistan, high wheat prices induced substitution away from nutrient-rich foods and, under severe constraints, Giffen-like behaviour (D'Souza & Jolliffe, 2012), consistent with evidence that very poor households may increase staple demand when rising prices force them away from more nutritious foods (Jensen & Miller, 2008). Evidence from urban Ethiopia and the 2007-2008 crisis similarly shows that price increases reduce diet quality even when calorie losses are moderate (Alem & Soderbom, 2012; Brinkman et al., 2010; Ruel et al., 2010; Attanasio et al., 2013).

Dietary adjustments often accompany coping strategies that smooth consumption temporarily but weaken resilience. Households may reduce meal frequency or portion sizes, defer health and education expenditures, borrow, seek informal assistance, increase labour supply, rely on remittances, incur debt, or sell productive assets. Such responses protect current consumption at the cost of future resilience (Corbett, 1988; Dercon, 2002; Carter & Lybbert, 2012). Evidence from Nigeria and Benin is consistent with this mechanism (Amolegbe et al., 2021; Nonvide et al., 2025). Remittances and transfers may buffer against food price inflation, but their effectiveness depends on networks and on whether the originating shocks are idiosyncratic or covariate (Mohapatra et al., 2012; Schindler, 2010).

These responses are embedded in local market structures. Households are affected by how price changes pass through the markets where they buy food and sell output, labour, or assets. Market integration, connectivity, transport costs, storage, trader behaviour, information flows and vertical coordination shape exposure to adverse movements and the ability to benefit from favourable ones. Poor connectivity may prevent producers from capturing higher prices or consumers from benefiting when prices fall; high integration may transmit originating shocks across the value chain rapidly while facilitating arbitrage and market access.

Market position alone is therefore insufficient to predict the impact of food price spikes on food security. Sehgal (2024) finds that Malawian smallholders initially benefit from seasonal maize price increases but later lose part of those gains when they return to the market as buyers. Onumah et al. (2024) and Abdi et al. (2024) show that market access, connectivity and institutional quality condition households' ability to maintain diet quality and capture gains from higher agricultural prices. These findings motivate attention to market integration, connectivity, and price-transmission efficiency, because asymmetric or incomplete pass-through can expose households to rapid retail increases while preventing proportional farm-gate gains or relief when upstream prices fall (Meyer & von Cramon-Taubadel, 2004; Chou & Lin, 2019; Gedara Korale et al., 2015).

2.1.3. Level of analysis

At the global level, studies of the 2007-2008 and 2010-2011 surges combine international price changes with household survey data to estimate first-round effects on real income, poverty, and food access. Ivanic & Martin (2008) show that short-run poverty effects vary by commodity and country, but poverty increases are more frequent and larger than reductions; De Hoyos & Medvedev (2011) and Wodon & Zaman (2010) reach similar conclusions for developing countries and Sub-Saharan Africa. For 2010-2011, Ivanic et al. (2012) estimate sizeable, short-run poverty increases across low- and middle-income countries. Yet welfare effects are ambiguous: producers may benefit when higher prices reach farm-gate prices, wages, or rural non-farm demand (Aksoy & Isik-Dikmelik, 2008; Headey & Martin, 2016), and higher real food prices can reduce poverty in agrarian economies when production and wage responses are strong (Headey & Hirvonen, 2023).

Nutrition-oriented evidence shows that food price surges affect diet quality as well as calories. Nutritious diets are more expensive than subsistence diets, and their affordability depends on retail prices and market access (Bai et al., 2021). Laborde et al. (2021a) show that COVID-19 increased the unaffordability of healthy and nutrient-adequate diets, while Laborde et al. (2021b) link the pandemic to higher poverty, food insecurity, and deteriorating diets through income losses and supply-chain costs. Headey & Ruel (2023) find that food inflation increases child wasting, especially among poor, rural, and landless households, consistent with evidence that food, fuel, and financial shocks reduce dietary diversity and nutritional quality among the poor (Ruel et al., 2010; Compton et al., 2010).

At the country level, evidence from the 2007-2008 crisis documents reductions in food access, dietary diversity, and nutritional quality, though effects differ by livelihood group and institutional setting. Studies report deteriorations in Burkina Faso (Prevel et al., 2012), calorie and nutrient intake in Afghanistan (D'Souza & Jolliffe, 2012), welfare among rural and urban households in Mexico, especially net maize buyers (Gonzalez Davila, 2010; Attanasio et al., 2013), and food security among landless and marginal farmers in Bangladesh (Akter & Basher, 2014). Latin American evidence also points to sizeable losses among poor consumers once substitution and domestic price transmission are considered (Robles & Torero, 2010). However, in Vietnam, Vu & Glewwe (2011) find that higher prices raised average welfare because gains for net sellers exceeded average losses, even though most households were worse off.

At the subnational level, national averages may mask spatial variation in exposure and impacts. Local food budget shares, production systems, transport costs, market access, and pass-through to retail and farm-gate prices shape the prices households face. Dhar et al. (2024) show that responses to global grain and edible-oil price shocks in Nigeria vary across regions and income groups, while Onumah et al. (2024) find that market access mediates the effect of maize price shocks on food expenditure and diet composition in Ghana. Spatial evidence on climate shocks reaches a similar conclusion for Nepal, where floods, landslides, droughts, and storms generate heterogeneous welfare and undernourishment effects across districts (Baptista et al., 2023). This evidence highlights local market structures but rarely links welfare directly to the price-transmission processes through which shocks are amplified or dampened.

2.2. The role of market integration and price transmission

The literature reviewed in Section 2.1 shows that the welfare effects of food price spikes cannot be inferred from households' market position alone. They also depend on how price signals move across space and along food supply chains. Market integration captures the extent to which spatially separated markets, or different segments of a value chain, are linked by arbitrage and share a long-run equilibrium. Price transmission describes how shocks in one market or supply-chain segment are reflected in another. These relationships are commonly studied through spatial price analysis, cointegration, and error-correction models, which distinguish the completeness, speed, and symmetry of adjustment (Ravallion, 1986; Fackler & Goodwin, 2001; Rapsomanikis et al., 2006; Meyer & von Cramon-Taubadel, 2004; von Cramon-Taubadel & Goodwin, 2021).

2.2.1. Market integration and price transmission in food markets

Food markets are rarely perfectly integrated. Price co-movement is shaped by transaction, transport and storage costs, market power, information frictions, quality differences, policy interventions and exchange rates. International price spikes therefore need not translate one-for-one into domestic prices, nor do domestic shocks pass uniformly from wholesale to retail or from retail back to farm-gate prices. Pass-through determines how shocks are allocated across consumers, farmers, traders, and retailers.

The market-integration literature starts from the idea that arbitrage links spatial prices once transfer costs are considered. Ravallion (1986) provided an influential framework for testing whether shocks in a central market are transmitted to local markets, while Fackler & Goodwin (2001) clarified the distinction between price co-movement, trade flows and market efficiency. Subsequent work cautions against inferring integration mechanically from correlation or cointegration. Barrett (2001) and Barrett & Li (2002) show that prices may appear linked when trade is constrained, and that trade may occur without full price convergence when transaction costs, risk, credit constraints and policy barriers limit arbitrage. This is especially relevant in developing-country food markets, where households face thin markets and uneven access to buyers, sellers and information.

Rapsomanikis et al. (2006) link market integration to price transmission through the completeness and speed with which shocks move through food and cash-crop markets. Integration is therefore not only whether prices share a long-run relationship, but also how quickly deviations are corrected. Error-correction models are relevant because the error-correction term captures adjustment toward long-run equilibrium. Slow or incomplete adjustment can leave local prices disconnected from upstream or benchmark prices long enough to affect production and consumption decisions and to distribute gains and losses unevenly.

Empirical evidence confirms that pass-through is heterogeneous and often incomplete. Minot (2011), using more than 60 price series from 11 Sub-Saharan African countries, shows that world food price changes are transmitted unevenly to domestic markets, varying by country, commodity, and location. Baquedano & Liefert (2014) find that consumer prices for major staples in developing countries are cointegrated with world prices only in some cases, and that exchange rates and local conditions shape adjustment. Ceballos et al. (2017) show that both price-level and volatility transmission from international to domestic grain markets are incomplete and context-specific. For household welfare, the relevant object is not the international or national shock itself, but the local price produced by the transmission process. This motivates treating local rice prices as outcomes of district-level integration, adjustment speed, and symmetry of pass-through.

2.2.2. Market connectivity, transaction costs, and local market structure

Market connectivity is the structural counterpart of market integration. Whereas integration is inferred from price dynamics, connectivity refers to the physical and institutional conditions that enable arbitrage: roads, distance to trading centres, transport services, storage, information flows, trader networks and competition. These factors determine both the prices households pay as consumers and the prices they receive as producers. Better-connected households may access more buyers, outlets and substitution opportunities, but also face faster exposure to adverse shocks. Remote households may be partly insulated, yet often face higher consumer prices, lower farm-gate prices and fewer gains from favourable movements.

Transaction costs create bands within which price differences persist without arbitrage. Goodwin and Piggott (2001) show that threshold effects are central to spatial market integration: adjustment may be weak when deviations are smaller than transaction costs, but faster once price gaps make trade profitable. This logic is relevant during crises, when fuel, working capital, transport or trader networks are disrupted. Information and transport frictions reinforce these effects. Aker (2010) shows that mobile-phone coverage reduced grain price dispersion in Niger, especially where transport costs were high, while Dillon & Barrett (2016) show for East Africa that oil prices affect local maize prices mainly through transport costs; in inland markets, fuel-cost pass-through can matter more than the world maize price itself.

In many low- and middle-income countries, the distance to economic centres is a meaningful measure of predetermined market exposure. It captures constraints affecting how quickly shocks reach local markets, whether producers can access buyers, and whether consumers can switch outlets or commodities. At the household level, Onumah et al. (2024) show that market access conditions the effect of maize price shocks on food expenditure and diet composition in Ghana, while Abdi et al. (2024) find that weak connectivity and institutional quality can prevent households from capturing gains from higher agricultural prices. Local market structure is thus a mechanism shaping exposure and adaptation, not simply a background condition.

2.2.3. Vertical price transmission and asymmetric adjustment along food supply chains

Related literature focuses on vertical price transmission along food supply chains. It links farm-gate, wholesale, and retail prices and determines how the impact of shocks on agrifood prices is distributed among producers, intermediaries, and consumers. In a competitive and frictionless chain, upstream and downstream prices should adjust proportionally after accounting for marketing costs and margins. In practice, prices may respond incompletely or with delays, and increases may be transmitted differently from decreases. This is the core concern of asymmetric price transmission (APT).

APT occurs when prices adjust differently to positive and negative shocks. A common food-market pattern is positive asymmetry: retail prices rise quickly when upstream price increase but fall slowly when upstream prices decrease. This may reflect market power, menu and adjustment costs, inventories, perishability, search costs, public interventions or imperfect competition (Goodwin & Holt, 1999; Abdulai, 2002; Meyer & von Cramon-Taubadel, 2004; Vavra & Goodwin, 2005; Frey & Manera, 2007). The effects are distributional as well as allocative: consumers face rapid pass-through of adverse shocks but delayed relief when upstream prices fall, while producers may not receive proportional gains when consumer prices rise.

Empirical findings on APT are context-specific. Meyer & von Cramon-Taubadel (2004) review its conceptual and econometric foundations, while Frey & Manera (2007) show that results depend on the type of asymmetry tested and the model used, including threshold and error-correction specifications. More recent reviews note that agricultural price relationships may be separated in space, time, and form, and that vertical coordination, contracting, and changing supply-chain organization make pass-through increasingly difficult to observe directly (von Cramon-Taubadel & Goodwin, 2021).

Rice-market evidence is especially relevant here. Gedara Korale et al. (2015) find evidence consistent with asymmetric transmission in Sri Lanka, suggesting that market structure and intermediary behaviour shape price movements along the chain. Chou & Lin (2019) show that asymmetric transmission in Taiwan's rice market can increase consumer costs. Because rice is both a major marketed crop and a staple, asymmetric wholesale-retail adjustment can affect households simultaneously as producers and consumers: during food inflation, they may face rapid increases in retail costs while receiving incomplete or delayed farm-gate gains.

Despite these theoretical and empirical insights, little is known about whether asymmetric transmission translates into measurable household food security outcomes, particularly among smallholder farmers who simultaneously participate in markets as consumers as well as producers.

3. Conceptual framework

The food price-shock literature documents heterogeneous household effects but often treats prices as given, while the price-transmission literature explains how shocks move across markets but rarely links pass-through to food-security outcomes. This reveals a main gap in the literature that we try to address in this study. This is done by linking the two strands of literature. On the one hand, we retain from the first strand of literature that food price shocks may affect household welfare through several pathways, translating these changes into consumption and nutritional outcomes. On the other hand, we borrow from the second strand of literature the insight that changes in prices at different levels in the food supply chain are crucially determined by the price transmission process, where asymmetric transmission (and change thereof) can play a critical role.

Consider a paddy-producing household that consumes rice and other foods, produces paddy, and may sell part of its output. Its food consumption depends on real purchasing power and on the income generated by paddy sales. An increase in the retail price of rice raises the cost of the staple consumption bundle and can reduce dietary quality, especially when demand for rice is inelastic and substitution toward cheaper calories or less diverse diets is limited. At the same time, a higher price of rice can increase welfare if it is transmitted to the farm-gate price and if the household sells enough paddy to offset the higher cost of food purchases. The net effect is therefore ambiguous ex ante and depends on the joint evolution of retail and farm-gate prices, not on retail inflation alone (Deaton, 1989; Singh et al., 1986; de Janvry et al., 1991).

Price transmission determines this joint evolution (Figure 1). In an integrated and competitive value chain, deviations between wholesale and retail prices are corrected quickly, and price changes are transmitted with limited delays after accounting for marketing costs. In imperfect markets, transaction costs, transport constraints, credit frictions, trader concentration, storage capacity, and information failures can make pass-through slow, incomplete or asymmetric. The error-correction term (ECT) summarizes the speed at which the retail-wholesale relationship returns to its long-run equilibrium after a shock; using its absolute value, a larger ECT indicates faster adjustment and stronger short-run transmission. A shock-induced change in the ECT, therefore, captures a change in the local mechanism through which national or upstream disturbances are converted into retail prices (Ravallion, 1986; Goodwin & Piggott, 2001; Meyer & von Cramon-Taubadel, 2004; Rapsomanikis et al., 2006).

Market exposure determines which households are most affected by this transmission process. Distance from economic centres is a predetermined proxy for the cost of reaching markets, the density of trading relationships, access to buyers and sellers, and the speed with which information and arbitrage operate. Farms more connected to market centres are likely to face faster exposure to transmission shocks, while more remote ones may be partially insulated but also have a weaker ability to arbitrage, switch outlets or capture higher producer prices.

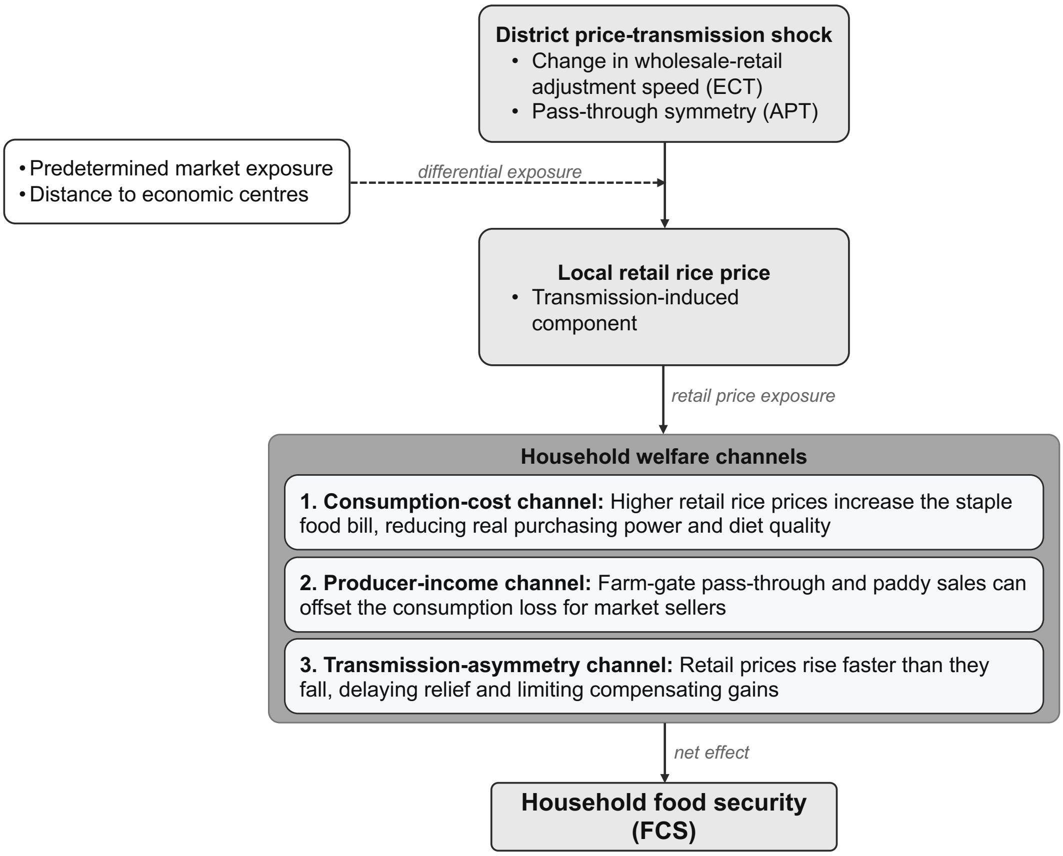

Figure 1: Conceptual framework linking rice price shocks, price transmission, and household food security.

Notes: ECT denotes the error-correction term measuring the speed of wholesale-retail price adjustment. Baseline distance to economic centres captures predetermined market exposure.

The framework also clarifies the expected mechanisms. The first channel is the consumption-cost channel: faster pass-through of adverse upstream movements raises retail rice prices and reduces real food purchasing power. The second is the producer-income channel: the negative consumption effect may be offset when higher downstream prices are transmitted to farm-gate prices and when the household sells enough paddy. The third is the transmission-asymmetry channel: when retail prices react more rapidly to wholesale increases than to decreases, households face rapid cost increases but delayed relief, and paddy producers may not receive proportional farm-gate gains. Under such conditions, market integration can magnify the vulnerability to shock-induced food price spikes rather than a coping mechanism (Meyer & von Cramon-Taubadel, 2004; Gedara Korale et al., 2015; Chou & Lin, 2019).

This conceptual framework yields three testable implications. First, an shock-induced increase in retail rice prices should reduce the food security (proxied by FCS) if the consumption-cost channel dominates any producer-income gains. Second, the effect should be concentrated among households with stronger market exposure, especially more commercialized paddy producers, because these households are more likely to be affected by retail and farm-gate price movements. Conversely, households with little or no market participation should serve as a placebo group: if the mechanism operates through price exposure, the estimated effect should be weaker or absent for relatively less commercial farmers. Third, food-security losses should be larger in districts where wholesale-retail pass-through is asymmetric, because positive asymmetry amplifies the retail burden of the shock while limiting compensating gains or relief.

Applied to Sri Lanka, the framework explains why a covariate exogenous shock can generate heterogeneous food-security outcomes among paddy producers. The 2022 crisis not only raised the level of rice prices; it also affected the transmission process through which wholesale, retail, and farm-gate prices adjusted. By treating local retail prices as an outcome of exogenous shock-induced district-specific variations in price transmission and predetermined farmer-specific market exposure, the empirical strategy links the price-transmission literature to the household food-security literature. It identifies whether the retail price component generated by transmission shocks causally reduced food security, and the heterogeneity checks test whether the estimated impact is consistent with the proposed mechanism.

4. Data and methods

4.1. Data description

The empirical analysis combines two primary sources of data. The first is a household panel survey of smallholder paddy-producing households conducted by the Agrifood Economics and Policy Division of the Food and Agriculture Organization of the United Nations (FAO). The second is a market-level price dataset compiled by the Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI), the premier national institute for socio-economic research on agriculture in Sri Lanka, which reports weekly food prices across Sri Lankan markets. Combining these sources allows to link household-level information on rice farming and food-security outcomes to local rice-price dynamics and district-level price-transmission measures.

The FAO dataset consists of a panel of 2,200 paddy-producing households, corresponding to approximately 0.3% of Sri Lanka's paddy farming population. The panel consists of three balanced waves.[5] Most of the households interviewed at the baseline were successfully re-interviewed in the two subsequent waves, resulting in 4% panel attrition across the three waves. For the present analysis, we retain households observed in the first two waves coinciding with the period of most severe food-price inflation, which is the most relevant for identifying the welfare effects of the crisis and for which there is no missing information on the Food Consumption Score, rice prices, and the set of household-level covariates used in the empirical model.

Data were collected through Computer-Assisted Personal Interviewing (CAPI). The sampling design followed a three-stage stratified cluster procedure, with stratification and probability-proportional-to-size sampling at each stage, to ensure nationally representativeness of paddy farmers. In the first stage, Sri Lanka's 25 districts were

[5] The first two waves cover the whole calendar years of 2022 and 2023, encompassing both *Maha* and *Yala* agricultural seasons. The third wave focuses exclusively on the 2023–2024 *Maha* season.

stratified into dry, intermediate, and wet agroecological zones, ten districts were sampled according to their share of land under paddy cultivation. In the second stage, Farmer Organizations (FOs) were stratified by irrigation type, distinguishing between major irrigation schemes, minor irrigation systems, and rainfed areas, as access to irrigation plays a crucial role in shaping farming practices (Yapa et al., 2020). A total of 220 FOs were then randomly selected with probabilities proportional to size. In the third stage, paddy-producing households were randomly sampled within each selected FO. This design ensures coverage of the main rice-producing areas while accounting for agroecological and irrigation-related heterogeneity in paddy production.

Market-price data are obtained from HARTI. The dataset contains weekly price series for rice and other food commodities at different stages of the supply chain, including farmgate, wholesale, and retail prices. Because farmgate prices are only available in for three districts, they cannot be used as the main explanatory variable in the empirical analysis. We therefore focus on retail rice prices, which capture the prices faced by households as consumers and are consistently available across the study districts. The retail rice price variable used in the empirical model is constructed as the average retail price, expressed in Sri Lankan Rupees per kilogram, over the six weeks preceding each household interview. This timing reduces the influence of short-run price noise and better reflects the price environment relevant for recent household food consumption.

The HARTI price data are also used to construct district-level measures of wholesale–retail price transmission. We estimate district-specific error-correction terms (ECTs) from wholesale and retail rice-price series for 2022 and 2023.[6] The ECT captures the speed at which deviations from the long-run wholesale–retail price relationship are corrected. Since valid ECTs are negative, larger absolute values indicate faster adjustment towards equilibrium and stronger short-run price transmission. In the empirical analysis, we use the absolute value of the ECT and interact it with the predetermined distance between each FO meeting point[7] and the nearest economic centre, a government-established wholesale agricultural marketplace where farmers and collectors can sell their produce, including paddy, directly to wholesale buyers. In our case, all estimated error correction terms are negative, consistent with the assumption of convergence towards the long-run equilibrium between wholesale and retail prices. We therefore do not face issues related to positive or unstable ECT estimates, and no truncation or re-coding of the ECT was required (Engle & Granger, 1987).

Table 1 reports the variables used in the empirical analysis. The main outcome variable is the Food Consumption Score (FCS), a validated composite metric that captures the quality of household diet (WFP, 2008).[8] The empirical specifications include a set of

[6] The procedure to estimate district-specific ECTs and the estimated ECTs are reported in Appendix A.
[7] This approach is driven by logistical and methodological constraints that preclude the use of household-level distance measures. Given that farmers' fields are located close to the FO meeting point in almost all cases, this indicator serves as a valid proxy for farmers' remoteness from markets.
[8] FCS is a continuous indicator based on the weighted count of how many days specific food groups are consumed over the seven days preceding the interview. Below the thresholds values of 45 and 62, the score indicates poor or borderline food consumption, respectively.

household-level controls that may affect food security. Household size and child dependency ratio capture demographic pressures on consumption, while the age, gender, and education of the household head proxy for decision-making and consumption smoothing capacity. Household wealth is proxied by the household assets endowment, which is critical in determining the household resilience capacity (Carter & Barrett, 2006). Land ownership is captured by a dichotomous variable indicating if the household is the only owner of the plot. Production loss is a continuous variable representing the acre of cultivated land lost due to multiple shocks. Finally, access to financial instruments (i.e., credit, insurance), which are crucial for smoothing consumption during price fluctuations, is captured through a dummy variable.

Table 1. Variable description.

Variables	Definition	Type
FCS	Food consumption score	Continuous
Price	Retail price Rs/ Kg in the 6 weeks before interview	Continuous
ΔECT x Distance	Change in ECT value x distance between the FO's meeting point and the nearest economic centre (Km)	Continuous
Year	Year (2022 and 2023)	Dummy (2023 = 1)
HH size	Household size	Count
CDR	Child dependency ratio	Continuous
Head age	Age of the household's head	Continuous
Head gender	Gender household's head	Dummy (male = 1)
Head education	Education attainment of the household's head	Categorical (primary = 1, middle = 2, secondary =3)
Wealth	Asset wealth index (all assets)	Categorical (1st tercile = 1, 2nd tercile = 2, 3rd tercile = 3)
Land ownership	Household has sole ownership of the plot	Dummy (Yes = 1)
Production loss	Total area lost (acres)	Continuous
Finance	Household has access to loan credit or insurance	Dummy (Yes = 1)

4.2. Identification strategy and empirical estimation

We estimate the local average treatment effect of retail rice prices on household food security using an instrumental-variables strategy. In fact, retail rice prices may be endogenous to household food security because of local demand conditions (de Janvry et al., 1991), unobserved market characteristics, and measurement error in aggregated price data (Gibson & Kim, 2013) that may generate a correlation between observed prices and unobserved determinants of the Food Consumption Score (FCS).

To address this concern, we exploit exogenous variation[9] in local price transmission generated by the 2022 crisis. Specifically, we construct an interacted a Bartik-like

[9] Although the instrument is constructed from the district-level absolute value of the error-correction term, household fixed effects identify the effect from within-household changes over time. With two survey waves, this corresponds to crisis-induced changes in district-level ECT between 2022 and 2023.

exposure instrument that combines district-level changes in the speed of wholesale-retail price adjustment with predetermined differences in market remoteness of the Farmer Organizations (FO).[10] The instrument is defined as:

$$Z_{idt} = \Delta|ECT_{dt}| \times Dist_i \tag{1}$$

where $\Delta|ECT_{dt}|$ captures the shock-induced change in the absolute value of the district-level error-correction term, and $Dist_i$ denotes the baseline distance between the Farmer Organization (FO) meeting point and the nearest economic centre. Since valid error-correction coefficients are negative, larger absolute values indicate faster adjustment towards the long-run wholesale-retail equilibrium and therefore stronger short-run price transmission.

The identifying variation comes from the interaction between time-varying district-level changes in price transmission and predetermined differences in exposure to market frictions. When the originating shock is exogenous to local demand and food security, the variation it induces in the transmission term is plausibly assumed exogenous to contemporaneous food-security outcomes. The distance, fixed at baseline, is predetermined and absorbed in levels by the household fixed effects, so identification comes entirely from how the time-varying, shock-driven transmission term interacts with such a fixed exposure. Household fixed effects absorb all time-invariant household, Farmer Organization, and district characteristics, including the level of distance from economic centres. Year fixed effects absorb shocks common to all households.

Instrument relevance requires that changes in wholesale-retail price transmission affect local retail rice prices differentially across households with different levels of predetermined market exposure. We assess this condition through the first-stage estimates and standard weak-instrument diagnostics.

The exclusion restriction requires that, conditional on household fixed effects, year effects, and observed time-varying household characteristics, the instrument affects household food security only through its influence on local retail rice prices. As household fixed-effects absorb all time-invariant household and local market characteristics, identification comes from exogenous shock-induced changes in district-level transmission dynamics and within-household differential exposure to these transmission shocks.[11] This assumption would be violated if changes in price transmission interacted with distance also captured other endogenous time-varying

[10] Our approach is Bartik-like rather than a standard Bartik's shift-share design (Adao et al., 2019) as the shift component is not the external shock itself, but a district-specific measure of how the shock is transmitted through local markets. Moreover, whereas the shift is typically common across units in canonical Bartik applications, the ECT varies across districts and over time, generating heterogeneous transmission shocks across local markets.

[11] No household changes district between survey waves, implying that district membership is perfectly collinear with the household fixed effect. As a result, all time-invariant district-level heterogeneity is absorbed by the estimator.

shocks affecting remote households, such as differential access to fertilizer, transport disruptions, food assistance, or local labour-market conditions. Section 4.3 discusses these threats and the empirical checks used to assess their plausibility.

The proposed identification strategy is supported by evidence from recent market disruptions in Sri Lanka. Generale (2025)[12] documents a sharp deterioration in short-run market integration across the farmgate, wholesale, and retail segments of the rice supply chain during the 2022 crisis, reflected in substantially weaker and, in some cases, unbounded error correction terms. At the same time, price transmission became highly asymmetric, with retail prices responding more rapidly to wholesale price increases than to decreases. These developments suggest that the crisis affected not only the level of rice prices but also the mechanisms through which prices were transmitted along the supply chain.

Formally, the empirical strategy consists of a two-stage fixed-effects instrumental variables estimation. In the first stage, retail rice prices are regressed on the instrument and the set of covariates including the fixed effects:

Stage I:
$$P_{idt} = \alpha_1 + \pi Z_{idt} + X_{it}'\gamma + \mu_i + \tau_t + u_{idt} \ , \tag{2}$$

where P_{idt} is the retail rice price faced by household *i*, in district *d*, and year *t*; X_{it} is a vector of time-varying household controls; μ_i denotes household fixed effects; and τ_t denotes year fixed effects.

In the second stage, the estimated price variable obtained from the first stage, $\hat{P}_{idt}$, is used as regressor to estimate the impact of rice prices on household food security, measured through the Food Consumption Score:

Stage II:
$$FCS_{idt} = \alpha_2 + \beta \hat{P}_{idt} + X_{it}'\theta + \mu_i + \tau_t + \varepsilon_{idt} \ . \tag{3}$$

The coefficient of interest, β, captures the local average treatment effect (LATE) of retail rice prices on household food security on the subgroup of compliers under the identifying assumptions discussed above. Compliers are households whose retail price exposure is shifted by the instrument, $\Delta|ECT_{dt}| \times Dist_i$, the estimate should be interpreted as treatment effect for the price-exposed subpopulation rather than as the average effect for all paddy-producing households.

Following best practice for shift–share designs and instrumental variables with estimated variables, we complement conventional inference with wild cluster bootstrap procedures where clusters are identified at the Farmer Organization level to match the instrument variability (Adao et al., 2019). The wild bootstrap standard error explicitly

[12] The results of Generale (2025) are summarized in Appendix B.

accounts for the estimation error embedded in the ECT, accounting for within-cluster correlation over time, and remains valid under a limited number of clusters.

4.3. Threats to identification

The validity of the instrumental-variable strategy depends on the assumption that changes in price transmission, interacted with predetermined distance from economic centres, affect household food security only through local retail rice prices. Although this assumption cannot be tested directly, several potential threats can be assessed conceptually and empirically.

Supply-side confounding. The same shock that altered price transmission may also have affected agricultural productivity, input availability, or harvest outcomes. In that case, food security losses could reflect a production channel rather than the retail price channel identified by the instrument. We address this concern on three complementary grounds. First, we directly control for household-level production losses, measured as cultivated land that was not harvested. Second, household fixed effects absorb time-invariant differences in land quality, production capacity, and local agroecological conditions, while year fixed effects absorb aggregate input and macroeconomic shocks common to all households. Third, and most importantly, in Sri Lanka fertilizer distribution has historically been administered through a centralized government subsidy scheme, with allocation and release timing set by the Ministry of Agriculture and channelled through the Agrarian Development Department and cooperatives, tied to the *Maha* and *Yala* seasons rather than to contemporaneous market price signals. This makes fertilizer availability administratively determined and plausibly exogenous to district-level price adjustment dynamics.[13] Nevertheless, the exclusion restriction would still be threatened by time-varying district-level shocks that are correlated with both price transmission and household food security. For this reason, the results should be interpreted together with the mechanism-based heterogeneity tests reported below.

Remoteness-specific crisis effects. The interaction between ECT changes and distance may capture differential exposure of remote households to the crisis through channels other than retail rice prices. For example, remote households may have experienced greater transport disruptions, weaker access to food assistance, more limited access to fertilizer, or slower recovery in local market activity. These channels would violate the exclusion restriction if they affected FCS independently of retail prices. The household fixed-effects structure removes permanent differences in remoteness and local market access, but it cannot by itself eliminate all time-varying remoteness-specific shocks. This concern can be partly addressed by controlling for observed production losses and by testing whether the estimated effects are concentrated among households whose food security should be most sensitive to market-mediated price variation.

[13] The 2021-2022 organic-only fertilizer import ban, whose timing and scope were driven by foreign exchange constraints and policy considerations entirely unrelated to rice market price dynamics provides the most direct evidence of this administrative rather than market-driven nature of input supply shocks in this context.

Price expectations. Changes in price transmission may affect household expectations about future prices and thereby influence food consumption independently of current retail prices. This channel is unlikely to be the dominant mechanism for two reasons. First, the ECT is an econometric construct derived from market-level price series and not directly observed by households. Second, the FCS refers to food consumption during the seven days preceding the interview, while expectation-driven adjustments to savings, storage, and consumption plans are likely to operate over longer time horizons (Attanasio et al., 2013). More compellingly, if expectation formation were the main channel, similar effects would be expected across households with different levels of market participation. The fact that estimated effects are statistically significant among more commercialized producers (cf. section 5.3.3) is consistent with a price-transmission mechanism than with a general expectations channel.

Reverse causality. Reverse causality would arise if household food consumption affected local retail prices or the estimated ECT. This is unlikely in the present setting because the ECT is constructed from district-level wholesale and retail price series, whereas the analysis focuses on smallholder rice-producing households whose individual consumption decisions are too small to affect district-level price adjustment dynamics (Wijesooriya et al., 2021).[14] In addition, the transmission measure is based on lagged price dynamics rather than contemporaneous household behaviour, further reducing the likelihood that current FCS determines the instrument.

Non-food budget reallocation. A final concern is that the instrument may capture broader local economic uncertainty rather than retail rice price variation alone. In that case, households could reduce food consumption because of precautionary saving or reallocations toward non-food expenditures, rather than because of higher rice prices. These concerns are less binding if the estimated welfare losses are concentrated among households with greater market exposure. These tests do not prove the exclusion restriction, but they provide evidence consistent with the proposed retail price-transmission channel.

For most of these threats, the heterogeneity analysis by market participation and by asymmetric price transmission provides mechanism-based evidence supporting the identification assumption (cf. section 5.3.3).

5. Results

5.1. Descriptive statistics

Table 2 reports descriptive statistics for the estimation sample, separately for 2022 and 2023 and for the pooled panel. The main outcome variable, the FCS, increased

[14] The ECT is constructed from regional price aggregates reflecting market-wide adjustment behaviour rather than localized household demand shocks, and identification relies on within-household variation over time, so reverse causality would require year-to-year changes in individual consumption large enough to systematically shift district-level price transmission, which is very unlikely given the scale of smallholder operations relative to district markets.

substantially from 65.12 in 2022 to 78.69 in 2023, with a pooled mean of 71.91. This pattern is consistent with an improvement in food consumption conditions after the peak of Sri Lanka's 2022 crisis. However, the increase should be interpreted descriptively, as it may reflect several contemporaneous factors, including easing food-price pressures, improved harvest conditions, recovery in supply-chain functioning, and policy responses.

Retail rice prices declined only modestly over the same period, from 219.24 Rs/kg in 2022 to 214.12 Rs/kg in 2023, with a pooled mean of 216.68 Rs/kg, indicating that the adjustment is relatively slow from year to year. The observed co-movement between lower retail prices and higher FCS is consistent with the mechanism tested in the empirical analysis.

Table 2: Descriptive statistics.

Variables	2022			2023			Pooled		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
FCS	1881	65.12	18.30	1881	78.69	18.09	3762	71.91	19.41
Price (Rs/kg)	1881	219.24	3.18	1881	214.12	3.51	3762	216.68	4.21
HH size (n)	1881	4.03	1.45	1881	4.05	1.47	3762	4.02	1.46
CDR	1881	23.34	33.71	1881	22.07	35.29	3762	22.76	25
Head age (years)	1881	56.35	11.81	1881	57.11	11.98	3762	56.73	11.93
Head gender (M=1, %)	1881	0.90	0.29	1881	0.89	0.30	3672	0.90	0.30
Head educ, Primary (%)	1881	16%	-	1881	17%	-	3672	17%	-
Head educ, Middle (%)	1881	21%	-	1881	20%	-	3672	21%	-
Head educ, Secondary (%)	1881	58%	-	1881	57%	-	3672	59%	-
Head educ, Bachelor (%)	1881	4%	-	1881	5%	-	3672	4%	-
Asset wealth	1881	0.00	1.01	1881	0.11	1.01	3762	0.00	1.01
Land ownership (Y=1, %)	1881	0.85	0.35	1881	0.87	0.33	3762	0.86	0.34
Production loss (acres)	1881	0.20	2.02	1881	0.25	0.96	3762	0.23	1.58
Finance (Y=1, %)	1881	0.31	0.46	1881	0.19	0.39	3672	0.25	0.43

Household characteristics are broadly stable across the two survey waves. Average household remains close to 4 members, the mean age of the household head is approximately 57 years, and around 90%of the households are male-headed. The child dependency ratio remained relatively stable, but its high dispersion suggests meaningful heterogeneity in household demographic pressure and potential nutritional vulnerability. Educational attainment is also stable, with most household heads having completed secondary education and only a small share holding a bachelor's degree. These patterns indicate that the panel composition is relatively stable over the two-year period.

Asset-related variables show limited variation. The asset wealth index is centred around zero by construction, while land ownership remains high, increasing slightly from 85% in 2022 to 87% in 2023. This small change should be interpreted cautiously, given the short time span of the panel. Production losses increased slightly, from 0.20 to 0.25 acres, although the high standard deviation in 2022 indicates substantial heterogeneity in households' exposure to shocks. Access to financial instruments declined from 31% in 2022 to 19% in 2023. This may reflect reduced access to credit, insurance, or other financial mechanisms after the crisis, although the descriptive statistics alone do not allow to identify the underlying mechanism.

Table 3 reports district-level descriptive statistics for the FCS. Mean FCS values are relatively similar across districts, ranging from 68.7 in Badulla to 73.7 in Kurunegala, with no clear spatial pattern or clustering of low food security. Within-district dispersion is much larger than between-district differences in means: standard deviations range from 16.2 to 22.5, while the difference between the lowest and highest district mean is approximately five points. This suggests that variation in food consumption is driven primarily by within-district household heterogeneity rather than by large average differences across districts. The absence of a clear spatial concentration of low FCS is reassuring, but it does not rule out time-varying district-level confounding. These concerns are addressed through the fixed-effects structure and the instrumental-variable strategy.

Table 3: Food consumption score per district.

District	Mean FCS	SD FCS	N
Ampara	73.40	22.49	408
Anuradhapura	72.57	19.40	430
Badulla	68.69	21.58	418
Batticaloa	72.62	18.06	420
Galle	71.70	19.54	428
Kilinochchi	71.18	16.17	428
Kurunegala	73.69	18.90	418
Mathara	70.15	20.63	420
Vavuniya	73.35	16.67	392

5.2. OLS estimate

Table 4 reports pooled OLS estimates of the association between retail rice prices and household food security, measured by the Food Consumption Score (FCS). These estimates provide a statistical benchmark for the instrumental-variable analysis that follows. The coefficient of price is negative and highly significant: a one Sri Lankan Rupee increase in retail rice prices is associated on average with a 0.23-point reduction in the FCS. This association is consistent with the hypothesis that higher staple-food prices reduce household food consumption. However, it should be interpreted with caution since local rice prices may be endogenous to unobserved household, market, or district-level conditions affecting food security.[15]

[15] This bias arises when one or more of the classical linear regression assumptions are violated, most notably, the assumption that the regressor is exogenous, or uncorrelated with the error term. In such cases, OLS yields biased and inconsistent estimates of the causal effect. Comparing the OLS and IV estimates not only improves causal inference but also offers insights into the underlying data-generating process and the severity of endogeneity in the model. However, while some difference between the OLS

The year dummy is positive and highly significant, indicating that FCS values were substantially higher in 2023 relative to 2022, conditional on the included controls. This pattern is consistent with the descriptive evidence reported above and likely reflects a broader recovery in food consumption conditions after the peak of the 2022 crisis (FAO & WFP, 2023). However, the year dummy captures all common changes between the two survey rounds and therefore cannot be attributed to any single mechanism.

Table 4: OLS results (dependent variable: FCS).

Variables	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price	-0.23	0.08	-2.70	0.00	-0.40	-0.06	***
2023	12.05	0.74	16.24	0.00	10.60	13.51	***
HH size	0.47	0.21	2.19	0.02	0.05	0.89	**
CDR	0.03	0.01	3.23	0.00	0.01	0.05	***
Head age	0.11	0.02	3.84	0.00	0.05	0.17	***
Head gender	1.49	1.02	1.45	0.14	-0.52	3.50	
Head education level							
Primary	-0.27	2.19	-0.13	0.898	-4.57	4.01	
Middle	1.16	2.17	0.54	0.591	-3.09	5.44	
Secondary	4.90	2.12	2.31	0.02	0.74	9.09	**
Asset wealth							
Middle	2.34	0.73	3.20	0.00	0.91	3.78	***
High	7.17	0.74	9.66	0.00	5.72	8.63	***
Land ownership	1.97	0.85	2.30	0.02	0.29	3.65	**
Production loss	-0.04	0.18	-0.24	0.81	-0.40	0.31	
Finance	-2.02	0.68	-2.98	0.00	-3.35	-0.69	***
Constant	-24283	1513	-16.04	0.00	-27251	-21315	***
Mean dependent var		71.986		SD dependent var			19.310
R-squared		0.195		Number of obs			3579
F-test		57.713		Prob > F			0.000
Akaike crit. (AIC)		30601.452		Bayesian crit. (BIC)			30700.377

*** p<.01, ** p<.05, * p<.1

Several household-level characteristics are significantly associated with FCS outcomes. Larger households and households with higher child dependency ratios report higher FCS values, although these coefficients should be interpreted as conditional correlations rather than structural effects. Household head age is positively associated with FCS, while head gender is not statistically significant. Education is generally positively associated with food consumption, especially at higher levels of schooling.

Access to financial instruments is negatively associated with FCS. This should not be interpreted as evidence that credit or insurance reduces food security. Rather, in Sri Lanka it is likely to capture farmers reliance on borrowing or insurance as ex-post coping mechanisms in response to adverse shocks. This interpretation is consistent

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and IV in the price coefficients can be expected, a substantial deviation between the two estimates may raise concerns about the exclusion restriction, model specification, or heterogeneity in treatment effects.

with the additional evidence reported in Appendix C, which suggests that financial access does not simply proxy for higher household wealth.[16]

Finally, as expected, we also observe a positive association between wealth and food security: households in the middle and upper wealth tertiles report higher and monotonically increasing food consumption scores.

Overall, the OLS results provide suggestive evidence of a negative relationship between retail rice prices and household food security. Nevertheless, because retail prices may be measured with error and correlated with unobserved determinants of FCS, the OLS estimates should be treated as a benchmark rather than as causal estimates. The instrumental-variable strategy addresses these concerns by isolating variation in retail prices generated by changes in price-transmission dynamics.

5.3. IV estimate

To address potential endogeneity concerns discussed above, we estimate a fixed-effect instrumental variable model in which retail rice prices are instrumented using the interaction between the district-level price-transmission dynamics and predetermined distance from the nearest economic centre (FOs). This strategy captures the component of retail rice price variation attributable to changes in local price transmission during the crisis, rather than to household-level demand conditions or unobserved food-security determinants.

5.3.1. First-stage estimate

Table 5 reports the first-stage estimates. The coefficient of the instrument, *ΔECT x Distance*, is positive and statistically significant, indicating that changes in wholesale-retail price-transmission speed are strongly associated with retail rice prices. This finding is consistent with the identification strategy: districts experiencing stronger short-run transmission between wholesale and retail prices also display higher retail rice prices, with the effect varying according to predetermined market remoteness.

The weak-instrument diagnostics support the relevance of the instrument. The first-stage F-statistic is well above conventional critical values, and the under-identification test rejects the null that the model is under-identified. These results indicate that the instrument has substantial predictive power for retail rice prices. These diagnostics speak to instrument relevance, not to the validity of exclusion restriction which in our analytical framework is not directly testable and is supported on theoretical and indirectly through a falsification test presented below and the placebo test which is integral part of the heterogeneity analysis.

The fixed-effects structure is central to this interpretation. Household fixed effects absorb all time-invariant households, FOs, and district characteristics, including

[16] We tested this hypothesis by, first excluding the possibility of a positive association between financial access and household wealth (Schindler, 2010) and then regressing the access to financial instrument on the price received for rice retrieving a negative and statistically significant coefficient while, in a context where access to financial services allows productive investment, we would have expected the opposite sales (Stephens & Barrett, 2011).

permanent differences in remoteness and market access. In addition, we find suggestive evidence supporting the exclusion restriction assumption.[17] Our falsification test highlights a statistically significant coefficient when we regress ECT against FCS, while, when retail prices are controlled for, the ECT-associated coefficient in the FCS equation turns out to be not statistically different from zero.

Importantly, as identification comes from changes in district-level price-transmission dynamics over time, interacted with predetermined exposure to market frictions, the first stage links the empirical strategy directly to the conceptual framework: retail prices are treated not as exogenous market outcomes, but as the result of local transmission processes shaped by crisis-induced disruptions.

Table 5: FE-IV results, first stage regression (dependent variable: price).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
ΔECT x Distance[a]	0.35	0.06	5.33	0.00	0.22	0.48	***
2023	-5.25	0.33	-15.66	-0.00	-5.94	-4.58	***
HH size	0.07	0.10	0.77	0.44	-0.12	0.28	
CDR	-0.00	0.00	-0.86	0.39	-0.01	0.00	
Head age	0.00	0.02	0.15	0.88	-0.04	0.05	
Head gender	-0.79	0.50	-1.55	0.12	-1.79	0.21	
Head educ. level							
Primary	1.21	0.67	1.81	0.07	-0.11	2.54	*
Middle	0.39	0.59	0.66	0.51	-0.78	1.56	
Secondary	0.72	0.54	1.34	0.18	-0.34	1.79	
Asset wealth							
Middle	-0.52	0.27	-1.87	0.06	-1.07	0.03	*
High	0.27	0.32	0.86	0.38	-0.35	0.91	
Land ownership	-0.16	0.21	-0.75	0.45	-0.59	0.26	
Production loss	0.00	0.11	0.07	0.94	-0.21	0.23	
Finance	0.41	0.22	1.88	0.06	-0.02	0.85	*
Constant	10833.23	677.82	15.98	0.00	9492	12173	***
Mean dependent var		216.691	SD dependent var			4.153	
R-squared		0.662	Number of obs			2459	
F-test		26.372	Prob > F			0.000	
Akaike crit. (AIC)		10011.595	Bayesian crit. (BIC)			10092.900	

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *ECT x Distance* t(133) = 5.3294 (*p* = 0.000).

5.3.2. Second-stage estimates

Table 6 reports the second-stage estimates. The coefficient on retail rice prices is negative and statistically significant. A one-rupee increase in retail rice prices reduces the FCS by 1.16 points. This estimate is larger in absolute value than the corresponding OLS coefficient of -0.23. This difference suggests that the OLS estimate may understate the welfare cost of rice-price increases, possibly because of measurement error in local price data or omitted factors that attenuate the observed

[17] See Appendix D for the exclusion restriction tests.

association.[18] However, the larger IV estimate may also reflect the local nature of the IV estimand: the coefficient captures the effect for households whose retail price exposure is shifted by transmission-induced price variation.

Table 6: FE-IV results, second stage regression (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	-1.16	0.57	-2.03	0.04	-2.29	-0.03	**
2023	8.18	2.93	2.79	0.00	2.43	13.93	***
HH size	0.49	0.57	0.87	0.38	-0.62	1.621	
CDR	0.01	0.03	0.47	0.63	-0.05	0.09	
Head age	-0.06	0.11	-0.53	0.59	-0.30	0.17	
Head gender	2.05	3.34	0.61	0.53	-4.50	8.60	
Head education level							
Primary	-2.47	3.49	-0.71	0.47	-9.31	4.36	
Middle	-5.41	3.37	-1.61	0.10	-12.02	1.19	
Secondary	-5.75	2.77	-2.07	0.03	-11.99	-0.31	**
Asset wealth							
Middle	2.59	1.14	1.83	0.06	-0.18	5.38	*
High	3.68	1.87	1.97	0.05	0.01	7.35	*
Land ownership	-0.54	1.33	-0.41	0.68	-3.15	2.06	
Production loss	1.34	0.49	2.74	0.00	0.38	2.31	***
Finance	-1.27	1.30	-0.98	0.38	-3.82	1.27	

Number obs	2390	Kleibergen–Paap LM statistic	11.30
Number of clusters	134	Cragg–Donald Wald F	185.73
F-statistic	30.76	Kleibergen–Paap rk Wald F	28.40
Centred R-squared	0.32	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	15.3		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: Price (t) = -2.0277 (p = 0.01).

The result is consistent with the consumption-cost channel described in the conceptual framework. Higher retail rice prices increase the cost of the staple consumption bundle and reduce real food purchasing power. Since the estimated coefficient is negative, the evidence suggests that this consumption-cost effect dominates any producer-income gains from higher rice prices for the households whose exposure is shifted by the instrument. This interpretation is particularly relevant in the Sri Lankan context, where paddy-producing households are both producers and consumers, and where higher retail prices may not translate proportionally into higher farmgate prices.

The year dummy remains positive and statistically significant, indicating that FCS was higher in 2023 than in 2022 2022 after controlling for retail prices and household covariates. This coefficient should be interpreted as capturing common changes

[18] For instance, informal community support mechanisms, in-kind transfers, or delayed consumption responses may all reduce the estimated magnitude of price effects, thereby underestimating the true welfare cost of rice inflation.

between the two survey rounds, including post-crisis recovery and improvements in food consumption conditions, rather than as evidence for a specific mechanism.

Overall, the IV estimates provide evidence that the component of retail rice-price variation generated by local price-transmission dynamics had a substantial negative effect on household food security. This finding supports the central mechanism of the paper: food-price shocks affect household welfare not only through the level of prices, but also through the way shocks are transmitted along the rice value chain. The following heterogeneity analysis by market participation and asymmetric price transmission is therefore essential for assessing whether the estimated average effect is concentrated among the households that are more commercial, as assumed in the conceptual framework.

5.4. Heterogeneity Analysis and Mechanism Validation (Placebo test)

The conceptual framework yields two mechanism-based predictions that can be assessed empirically. First, if the estimated IV effect operates through market-mediated retail price exposure, it should be stronger among households that are more commercially engaged in rice markets. Second, if asymmetric price transmission amplifies the welfare cost of food-price shocks, the effect should be concentrated in districts where wholesale-retail pass-through became asymmetric during the crisis. The heterogeneity analysis therefore serves two purposes: it identifies which households are most affected by transmission-induced retail price variation and provides supporting evidence for the mechanism underlying the identification strategy.

We first examine heterogeneity by household market participation. Ideally, households would be classified as net buyers, net sellers, and self-sufficient producers using detailed information on rice purchases, sales, and own consumption. Since these data are not available in the panel, we use the share of paddy production sold as a proxy for commercialization. Households are classified as non-sellers if they report no rice sales, low-sellers if they sell less than 50% of production, and high-sellers if they sell more than 50%.[19]

The results are consistent with the market-exposure mechanism (Table 7).[20] The estimated coefficient is small (-0.48) and not statistically significant among non-selling households, larger (-1.98) but still not statistically different from zero among low-selling households, and largest (-3.53) and statistically significant at the 5% level among high-selling households. Consistent with the conceptual framework, households more exposed to rice markets are more affected by transmission-induced price variation, whereas households relying more on self-consumption are relatively more insulated.

[19] We partitioned the sample rather than using interaction terms, to avoid potential endogeneity arising from interacted covariates.
[20] The full set of results is presented in Appendix E.

Table 7: Heterogeneity analysis and mechanism validation.

Group	Price coefficient	Robust SE	p-value	N	Clusters	Kleiberger-Paap rk Wald F
Pooled	-1.16**	0.57	0.04	2,390	134	28.40
By paddy sales / commercialization						
Non-selling (Q sold = 0)	-0.48	0.56	0.38	844	99	10.39
Low-selling (Q sold < 50%)	-1.98	2.09	0.34	162	48	13.95
High-selling (Q sold > 50%)	-3.53**	1.72	0.04	468	67	19.27
By change in asymmetric price transmission[a]						
Symmetric to asymmetric (APT 0 to 1)	-3.16***	0.46	0.00	224	13	28.40
Asymmetric to symmetric (APT 1 to 0)	0.27	0.31	0.38	838	48	29.40

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[a] APT indicates short-run asymmetric price transmission, where 1 denotes asymmetric transmission and 0 denotes symmetric transmission.

Notes: Robust standard errors are clustered at the Farmer Organization level. Subgroup estimates should be interpreted together with the corresponding first-stage diagnostics, especially where the number of observations or clusters is small.

This result also provides a mechanism-based placebo test. If the instrument captured alternative channels unrelated to retail prices, such as general crisis exposure, local labour-market disruption, or other remoteness-related shocks unrelated to retail rice prices, similar effects would be expected across households regardless of their degree of rice market commercialization. Instead, the concentration of effects among high-selling households is more consistent with the interpretation that the IV estimate operates through the retail price channel. This should not be read as definitive proof of the exclusion restriction, but it provides supporting evidence which is difficult to reconcile with alternative explanations.

The result is also informative about the balance between the consumption-cost and producer-income channels. In principle, more commercialized paddy producers could benefit from higher rice prices if retail price increases were transmitted proportionally to farm-gate prices. The negative and statistically significant effect among high-selling households suggests that this compensating producer-income channel was insufficient. For these households, the increase in retail food costs appears to dominate any gains from paddy sales, consistent with incomplete or delayed farm-gate pass-through during the crisis.

The second heterogeneity test is related to the functioning of markets themselves. Drawing on Generale (2025), districts are classified according to changes in short-run wholesale–retail asymmetric price transmission between 2022 and 2023. The key distinction is between districts that moved from symmetric to asymmetric transmission where retail prices began responding more rapidly to wholesale price increases than to decreases, and districts that moved from asymmetric to symmetric transmission.

The results provide strong evidence consistent with the transmission-asymmetry channel. In districts that shifted from symmetric to asymmetric transmission, a one-rupee increase in the instrumented retail rice price is associated with a 3.16-point decline in the FCS. Evaluated at the mean retail rice price, this corresponds to an approximately 6.86-point decline in FCS for a 1% increase in rice prices. By contrast, in districts that shifted from asymmetric to symmetric transmission, the estimated effect is small and statistically indistinguishable from zero.

Also, this pattern is directly aligned with the conceptual framework. When pass-through is relatively symmetric, households that both sell paddy and purchase food may partially offset higher consumer prices through improved transmission of price signals along the value chain. When pass-through becomes asymmetric, this balancing mechanism weakens: retail prices adjust rapidly to upstream price increases, raising the cost of food consumption, while offsetting gains or relief are delayed, incomplete, or absorbed along the chain.

Taken together, the two heterogeneity exercises support our central hypothesis. Food-security losses are concentrated among households with greater exposure to rice markets and in districts where price transmission became more asymmetric. These findings suggest that the welfare effects of food-price shocks depend not only on the level of retail prices, but also on how shocks are transmitted through local markets and households exposure to that transmission process.

6. Conclusions

This paper examines how food-price spikes affect household food security when the local market transmits exogenous compound shocks imperfectly. Using panel data on Sri Lankan paddy-producing households during the 2022 economic crisis, we estimate the causal effect of retail rice price surges on the Food Consumption Score through a fixed-effects instrumental-variable strategy. The instrument exploits changes in district-level wholesale–retail price-transmission speed, measured through the error-correction term, interacted with predetermined distance from economic centres. In doing so, the paper responds to recent calls for stronger causal identification in the food security literature (Alam et al., 2024) and links two strands of literature that are usually analysed separately: studies of food price shocks and household welfare, and studies of price transmission and market integration.

The results provide evidence that shock transmission-induced increases in retail rice prices significantly reduced household food security. A one-rupee increase in retail rice prices reduces the Food Consumption Score by 1.16 points on average. This finding is consistent with the consumption-cost channel: higher staple-food prices erode real purchasing power and reduce households' ability to maintain adequate and diverse diets. This mechanism is well established in agricultural household models literature (Singh et al., 1986; de Janvry et al., 1991), and in empirical work showing that food-price increases can reduce welfare and diet quality among vulnerable households (Ivanic & Martin, 2008; D'Souza & Jolliffe, 2012; Headey & Martin, 2016). The IV estimate is substantially larger than the OLS association, suggesting that standard estimates may understate the welfare cost of rice-price inflation when price variation is measured with error or correlated with unobserved local conditions, at least for the subgroup of *compliers* i.e. the farmers that are more exposed to the food price inflation sue to the variation of the transmission speed.

Consistently, the heterogeneity analysis clarifies the mechanism behind this average effect. Food-security losses are concentrated among highly commercialized paddy-producing households, while estimated effects for non-selling and low-selling households are smaller and statistically indistinguishable from zero. This pattern suggests that market participation can favour the transmission of the detrimental impact of exogenous shocks when they materialize as food price spikes. In principle, higher agricultural prices may benefit net sellers and stimulate rural incomes when price incentives are transmitted to producers (Aksoy & Isik-Dikmelik, 2008; Headey & Hirvonen, 2023). However, more commercialized households are also more exposed to retail and farmgate price movements. When retail price increases are not matched by proportional or timely gains at the farmgate level, the consumption-cost channel can dominate the producer-income channel, especially for smallholders who operate simultaneously as producers and consumers (Deaton, 1989; Barrett & Dorosh, 1996; Stephens & Barrett, 2011).

The results by transmission regime further support this interpretation. The negative effect of retail rice prices is concentrated in districts where wholesale–retail pass-through shifted from symmetric to asymmetric adjustment. In these markets, retail prices respond more rapidly to wholesale price increases than to decreases, exposing households to rapid increases in consumption costs while delaying relief when upstream prices fall. This is consistent with the literature on asymmetric price transmission, which shows that market power, transaction costs, storage constraints, information frictions, and adjustment costs can generate incomplete or asymmetric pass-through along agricultural value chains (Goodwin & Holt, 1999; Meyer & von Cramon-Taubadel, 2004; Vavra & Goodwin, 2005; Frey & Manera, 2007). By contrast, in districts where transmission became more symmetric, the estimated effect is small and statistically insignificant.

Altogether, these findings also support the argument that food price shocks operate not only through changes in price levels but also through the way those changes are transmitted along the supply chain.

From a policy perspective, the results imply that food security interventions should also address the functioning of local markets. Policies that improve market transparency, reduce transport and storage bottlenecks, strengthen competition along the rice value chain, and monitor asymmetric pass-through may be as important as traditional income-support measures or food assistance programmes (Laborde et al., 2021b; Dhar et al., 2024). This is consistent with the broader agricultural economics literature showing that transaction costs, infrastructure, information flows, and market connectivity shape both price transmission and household welfare outcomes (Fackler & Goodwin, 2001; Goodwin & Piggott, 2001; Barrett & Li, 2002; Aker, 2010; Dillon & Barrett, 2016). At the same time, safety-net and food-assistance programmes should recognize that commercially engaged smallholders can also be vulnerable when exogenous shocks determine food price spikes and the market pass-through across food value chain segments is incomplete or asymmetric.

Several limitations should be acknowledged, such as the lack of farmgate price data in some districts that prevented to fully tracing the joint evolution of retail and farmgate prices at the household level; or the lack of detailed information on rice purchases and own consumption that forced us to use rice sales as a proxy for net market position. Future research could build on our approach by combining household panel data with more granular farmgate, wholesale, and retail price series, as well as direct measures of household purchases, sales, and net food-market position to confirm or refute our findings. This is important to support or challenge our key conclusion: understanding and mitigating future food crises requires attention not only to the magnitude of price increases, but also to the mechanisms through which prices are transmitted across space, along value chains, and ultimately to households.

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Appendix A – Construction of district-level error correction terms

The Error Correction Terms (ECTs) are computed using the Vector Error Correction Model (VECM). The VECM is an econometric model specifically designed for analysing non-stationary time series that are cointegrated. When variables exhibit a long-run equilibrium relationship but are individually integrated of order one, *I*(1), the VECM enables the modelling of both short-term dynamics and long-term equilibrium adjustments within a unified system (Engle & Granger, 1987). VECM introduces an error correction term, which represents the adjustment process when variables deviate from their long-term equilibrium. This term captures short-term dynamics and is based on the differences (or changes) between the non-stationary variables and their cointegrating relationship.

The equations below describe the long-run equilibrium relationship between farm-wholesale and wholesale-retail prices:

$$F_t = \beta_0 + \beta_1 W_t + \Psi T + \varepsilon_t \quad \text{(A1)}$$

$$R_t = \theta_0 + \theta_1 W_t + \varphi T + \vartheta_t \quad \text{(A2)}$$

where F is the farm or producer price, W is the wholesale price, R is the retail price, T is the time trend variable, and ε and ϑ are Gaussian white noise error terms for the respective equation.

Consistent with the VECM literature on vertical price transmission, which assumes upstream prices are treated as weakly exogenous when the objective is to estimate downstream adjustment dynamics (Engle & Granger, 1987; Meyer & von Cramon-Taubadel, 2004), we assume that the wholesale price is weakly exogenous. This assumption reflects the vertical organization of the rice supply chain, in which wholesale markets serve as the principal channel through which upstream supply shocks are transmitted to retail markets, while retail prices adjust to deviations from the long-run equilibrium.

The short-run dynamic price adjustments modified by an ECT are specified in terms of a typical error correction model (ECM):

$$\Delta F_t = \mu_1 + \Sigma_{i=1}^{k} \beta_{i(f)} \Delta F_{t-i} + \Sigma_{i=0}^{l} \beta_{j(w)} \Delta W_{t-j} + \alpha_1 \hat{\varepsilon}_{t-1} + \varepsilon_t \quad \text{(A3)}$$

$$\Delta R_t = \mu_1 + \Sigma_{i=1}^{k} \theta_{i(r)} \Delta R_{t-i} + \Sigma_{i=0}^{l} \theta_{j(w)} \Delta W_{t-j} + \alpha_2 \hat{\vartheta}_{t-1} + \omega_t \quad \text{(A4)}$$

where, β_i and β_j measure the short-run effect of previous movements in farm and wholesale prices on current farm price changes, while θ_i and θ_j measure the same for retail and wholesale prices on current retail price changes. While α_1 and α_2 measure the speed of the adjustment to perturbations in long-run equilibrium; $\hat{u}_{t-1}$ and $\hat{v}_{t-1}$, the ECM terms, measure the size of the last period's departure (price perturbation) from the long-run equilibrium, where

$$\hat{u}_{t-1} = F_{t-1} - \beta_0 - \beta_1 W_{t-1} - \psi T$$

$$\hat{v}_{t-1} = R_{t-1} - \theta_0 - \theta_1 W_{t-1} - \varphi \mathrm{T}.$$

The estimated ECTs for the analysed district and year are reported in Table A1.

Table A1: ECTs by district and year.

District	Year	ECT
Ampara	2022	-0.25**
Ampara	2023	-0.18*
Anuradhapura	2022	-0.66***
Anuradhapura	2023	-0.60***
Badulla	2022	-0.28***
Badulla	2023	-0.24**
Batticaloa	2022	-1.03***
Batticaloa	2023	-0.47***
Galle	2022	-0.24***
Galle	2023	-0.69***
Kilinochchi	2022	-1.14***
Kilinochchi	2023	-0.34***
Kurunegala	2022	-0.22***
Kurunegala	2023	-0.49***
Mathara	2022	-0.49***
Mathara	2023	-0.64***
Vavuniya	2022	-0.10**
Vavuniya	2023	-0.21***

*** p<.01, ** p<.05, * p<.1

Appendix B – Vertical price transmission and asymmetric adjustment

Tables B1 and B2 present the results of the VECM for 2022 and 2023. They provide aggregate evidence on vertical transmission along the rice value chain, while the district-year ECTs used in the instrument are reported in Appendix A.

As we previously stated in 2022, Sri Lanka experienced peak rice and food prices alongside severe economic turmoil, including collapse, fuel shortages, and worsening food security. Error Correction Terms (ECTs) reveal contrasting dynamics. The wholesale–retail error correction term (−1.22) is statistically significant and indicates rapid but non-monotonic adjustment. The magnitude greater than unity implies that more than the full disequilibrium is corrected within one week, leading to short-run oscillations around the long-run equilibrium. This pattern is consistent with overshooting or non-monotonic adjustment during a period of extreme price volatility and uncertainty such as that observed during Sri Lanka's 2022 economic crisis, where retail prices likely overreacted to upstream shocks before stabilizing. In this case, the conventional half-life measure is not well-defined, as the speed of adjustment exceeds unity and implies oscillatory convergence rather than a smooth, monotonic return to equilibrium; therefore, reporting a half-life would be misleading (Abifarin et al., 2024). The wholesale–farmgate ECT shows a modest but significant 7% weekly adjustment. Finally, the retail-farmgate coefficient is low and not statistically significant, indicating a lack of short-term adjustment.

Table B1: Vertical integration 2022.

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.92***	-1.22***	-
Retail – Farmgate	0.46***	-0.05	13.51
Wholesale – Farmgate	0.49***	-0.07**	9.55

*** p<.01, ** p<.05, * p<.1

We now focus on 2023, a year in which rice prices and food prices more broadly remained elevated, while inflation began to ease and overall economic conditions showed signs of gradual improvement. Examining the ECTs, we observe that, across all levels of the supply chain, they lie between zero and one and are highly statistically significant. Moreover, there is a marked increase in the speed of adjustment moving from the Retail–Farmgate to the Wholesale–Farmgate segments. In contrast, the ECT for the Retail–Wholesale segment stabilizes below one.

Table B2: Vertical integration 2023.

Markets	Long Run Coefficient	ECT	Half-lives (weeks)
Retail – Wholesale	0.71***	-0.62***	0.71
Retail – Farmgate	0.29***	-0.32***	1.73
Wholesale – Farmgate	0.40***	-0.43***	1.23

*** p<.01, ** p<.05, * p<.1

To detect the presence and direction of Asymmetric Price Transmission, we employed the Non-Linear Autoregressive Distributed Lags model (NARDL). The model was developed by Shin et al. (2014), who expanded the Autoregressive Distributed Lag model (ARDL) to a nonlinear framework in which short- and long-run nonlinearities are introduced via positive and negative partial sum decompositions of the explanatory variable. NARDL models capture asymmetric price transmission both in speed and in magnitude by incorporating different adjustment coefficients for positive and negative shocks.

We start by looking at the standard ARDL (*p*, *q*), co-integration model (Pesaran & Shin, 1995) where *p* is the dependent variable, *q* is the independent variable, and we have two time series $\{y_t\}$ and $\{x_t\}$ (*t* = 1, 2, ..., *T*). This model has the following form:

$$\Delta_{yt} = \alpha_0 + \rho y_{t-1} + \theta x_{t-1} + \gamma z_t + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-1} + \sum_{j=0}^{q-1} \pi_j \Delta y_{t-1} + \varepsilon_t \quad \text{(B1)}$$

Shin et al. (2014) introduced the Nonlinear Autoregressive Distributed Lag (NARDL) model, where $\{x_t\}$ is decomposed into its positive and negative partial sums, as follows:

$$x_t = x_0 + x_t^+ + x_t^- \quad \text{(B2)}$$

where

$$x_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta_{j\,,}\, 0) \quad \text{(B3)}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta_{j\,,}\, 0). \quad \text{(B4)}$$

Then the long-run equilibrium relationship can be written as:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t. \quad \text{(B5)}$$

Shin et al. (2014) demonstrated that by integrating equation (B3) with the ARDL (*p*, *q*) model (B1), the NARDL (*p*, *q*) model is derived. In this model, β^+ and β^- represent the asymmetric long-run parameters associated with positive and negative changes in $\{x_t\}$, respectively:

$$\Delta y_t = \alpha_0 + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-1} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + e_t \quad \text{(B6)}$$

where

$\theta^+ = -\rho/\beta^+$ and $\theta^- = -\rho/\beta^-$.

Looking at Table B3, we observe that in 2022 there is clear evidence of positive asymmetric price transmission (APT) in both the short and the long run. To partition our sample, we focused on short-run APT to respect the temporality of both the outcome and the instrument.

Table B3: Asymmetric price transmission 2022.

Exogenous variables	**Long Run effect [+]**			**Long Run effect [-]**		
	Coef.	F-stat	p>F	Coef.	F-stat	p>F
Ln Wholesale → Ln Retail	0.95***	16549	0.00	-0.89***	2791	0.00
	Long Run asymmetry			**Short Run asymmetry**		
	F-stat		p>F	F-stat		p>F
Ln Wholesale → Ln Retail	28.63***		0.00	3.48*		0.06

*** p<.01, ** p<.05, * p<.1

Appendix C – Additional evidence on financial access

Tables C1 and C2 provide additional evidence to explain the negative association between financial access and food consumption outcomes. Table C1 shows that financial access is negatively and significantly associated with the price received for rice sales. Table C2 provides no evidence that access to financial instruments is positively associated with asset-based wealth, suggesting that finance does not simply proxy for greater economic capacity in this sample. The latter is confirmed by the estimation of marginal effects.

Table C1: Association between finance access and harvest price (OLS).

Rice price	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Finance	-3.31	1.47	-2.25	0.02	-6.20	-0.42	**
Constant	99.27	0.86	114.77	0.00	97.58	100.97	***
Mean dependent var		98.137	SD dependent var			30.123	
R-squared		0.003	Number of obs			1846	
F-test		5.059	Prob > F			0.025	
Akaike crit. (AIC)		17808.977	Bayesian crit. (BIC)			17820.019	

*** p<.01, ** p<.05, * p<.1

Table C2: Association between finance access and asset wealth (Probit).

Finance	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Asset wealth	-0.00	0.02	-0.19	0.84	-0.04	0.03	
Constant	-0.66	0.02	-30.09	0.00	-0.71	-0.62	***
Mean dependent var		0.252	SD dependent var			0.434	
Pseudo r-squared		0.000	Number of obs			3762	
Chi-square		0.038	Prob > chi2			0.845	
Akaike crit. (AIC)		4253.546	Bayesian crit. (BIC)			4266.011	

*** p<.01, ** p<.05, * p<.1

Table C3: Average Marginal Effects from Probit Model.

Variable	Coef.	Std. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Asset wealth	-0.0013436	0.0068937	-0.19	0.845	-0.01,	0.01	

*** p<.01, ** p<.05, * p<.1

Appendix D – Additional evidence on the exclusion restriction

The first-stage regression confirms that the *ΔECT* × *Distance* instrument is statistically relevant, providing a strong source of variation in retail rice prices for the second-stage analysis. The more important identifying assumption, however, is the exclusion restriction. Formally, this requires that, conditional on household fixed effects, year effects, and observed household characteristics, the transmission shocks captured by the instrument affect household food security only through their impact on local retail rice prices. Consequently, the instrument must be uncorrelated with unobserved determinants of food consumption. Potential alternative channels, such as changes in expectations, non-food expenditure decisions, or other behavioural responses, would threaten identification only if they affected food security independently of realized retail prices. The credibility of the empirical strategy therefore rests on the assumption that the variation in food security generated by short-run changes in transmission dynamics operates exclusively through the retail prices faced by households.

Empirically, we tested these assumptions by estimating regressions of FCS on the *ΔECT* × *Distance*, both with and without controlling for retail prices. The *ΔECT* × *Distance* is statistically significant in models without price controls (Table D1) but becomes insignificant once retail prices are included (Table D2). These results are consistent with the interpretation that the instrument affects FCS primarily through retail rice prices. However, they should not be interpreted as a direct test of the exclusion restriction, which remains an identifying assumption

Table D1: Exclusion restriction test, model without price (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
ΔECT x Distance[a]	-0.41	0.15	-1.87	0.06	-0.84	0.02	*
2023	14.29	0.67	16.63	0.00	12.59	15.99	***
HH size	0.40	0.56	0.72	0.47	-0.71	1.52	
CDR	0.02	0.03	0.63	0.53	-0.05	0.12	
Head age	-0.06	0.12	-0.52	0.60	-0.30	0.17	
Head gender	2.97	3.11	0.95	0.34	-3.19	9.13	
Head educ. level							
Primary	-3.88	3.56	-0.69	0.49	-12.98	6.25	
Middle	-5.25	3.32	-0.99	0.32	-15.79	5.28	
Secondary	-5.89	3.47	-1.08	0.28	-16.718	4.92	
Asset wealth							
Medium	3.19	1.51	2.12	0.03	0.20	6.18	**
High	3.35	1.87	1.78	0.07	-0.36	7.06	*
Land ownership	-0.35	1.32	-0.26	0.79	-2.97	2.27	
Production loss	1.34	0.48	2.78	0.00	0.38	2.29	***
Finance	-1.75	1.23	-1.42	0.15	-4.19	0.68	
Constant	-28849	1351.53	-21	0.00	-31516	-26181	***
Mean dependent var		71.821	SD dependent var				19.527
R-squared		0.310	Number of obs				2459
F-test		26.864	Prob > F				0.000
Akaike crit. (AIC)		18676.662	Bayesian crit. (BIC)				18763.775

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *ΔECT x Distance* (t) = -1.8679 (*p* = 0.03).

Table D2: Exclusion restriction test, model including price (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price	-0.73	0.17	-3.65	0.00	-1.13	-0.33	***
ΔECT x Distance[a]	-0.15	0.16	-0.71	0.47	-0.57	0.27	
2023	10.44	1.10	10.06	0.00	8.39	12.50	***
HH size	0.46	0.56	0.82	0.41	-0.65	1.58	
CDR	0.02	0.03	0.53	0.59	-0.05	0.09	
Head age	-0.06	0.12	-0.50	0.61	-0.30	0.18	
Head gender	2.39	3.20	0.75	0.45	-3.94	8.73	
Head educ. level							
Primary	-2.99	3.54	-0.57	0.57	-12.34	6.84	
Middle	-5.59	3.34	-0.99	0.32	-15.86	5.28	
Secondary	-5.83	3.43	-1.06	0.29	-16.48	5.01	
Asset wealth							
Medium	2.82	1.47	1.92	0.05	-0.08	5.72	*
High	3.56	1.86	1.91	0.05	-0.11	7.24	*
Land ownership	-0.47	1.33	-0.35	0.76	-3.11	2.16	
Production loss	1.34	0.48	2.77	0.00	0.38	2.30	***
Finance	-1.45	1.26	-1.15	0.25	-3.95	1.05	
Constant	-2093	2266.46	-9225.1	0.00	-25350	-16456	***

Mean dependent var	71.821	SD dependent var	19.527
R-squared	0.321	Number of obs	2459
F-test	28.969	Prob > F	0.000
Akaike crit. (AIC)	18639.361	Bayesian crit. (BIC)	18732.281

*** $p<.01$, ** $p<.05$, * $p<.1$

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *ΔECT x Distance* (t) = -0.7116 (*p* = 0.50).

Appendix E – Full heterogeneity estimates

Table E1 classifies the various districts according to the type of asymmetric transmission (after Generale, 2025).

Table E1: Short-run asymmetric price transmission by district and year.

District	Year	APT (1 = yes, 0 = no)	F-stat
Ampara	2022	0	0.20
Ampara	2023	0	0.97
Anuradhapura	2022	1	6.29
Anuradhapura	2023	0	2.47
Badulla	2022	0	0.33
Badulla	2023	0	1.08
Batticaloa	2022	1	3.65
Batticaloa	2023	0	1.22
Galle	2022	0	0.36
Galle	2023	0	0.97
Kilinochchi	2022	0	0.00
Kilinochchi	2023	0	0.76
Kurunegala	2022	1	9.42
Kurunegala	2023	0	0.10
Mathara	2022	0	0.62
Mathara	2023	1	3.47
Vavuniya	2022	0	0.68
Vavuniya	2023	1	3.99

The following tables report the result of the heterogeneity analysis, according to the paddy producer household engagement in rice selling activities (Table E2 to E4) and to switching the price transmission pattern between 2022 and 2023, from asymmetric to symmetric (Table E5) and from symmetric to asymmetric (Table E6).

Table E2: Heterogeneity Analysis and Mechanism Validation, non-selling paddy producer households (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	-0.48	0.56	-0.87	0.38	-1.59	0.61	
2023	10.99	1.86	5.90	0.00	7.34	14.64	***
HH size	2.32	0.90	2.58	0.01	0.55	4.08	**
CDR	0.00	0.05	0.12	0.90	-0.10	0.11	
Head age	0.23	0.18	1.24	0.21	-0.13	0.67	
Head gender	3.81	4.10	0.93	0.35	-4.23	11.85	
Head educ. level							
Primary	-7.09	6.74	-1.05	0.29	-20.30	6.11	
Middle	-6.05	7.82	-0.77	0.44	-21.34	9.33	
Secondary	1.50	7.72	0.19	0.84	-13.62	16.64	
Asset wealth							
Medium	3.77	1.82	2.07	0.03	0.20	7.34	**
High	2.33	2.55	0.91	0.36	-2.68	7.35	
Land ownership	1.55	2.40	0.65	0.51	-3.16	6.27	
Production loss	-1.41	1.11	-1.27	0.20	-3.59	0.77	
Finance	-0.43	2.47	-0.18	0.85	-5.28	4.41	

Number obs	844	Kleibergen–Paap LM statistic	11.3
Number of clusters	99	Cragg–Donald Wald F	59.29
F-statistic	15.56	Kleibergen–Paap rk Wald F	10.39
Centred R-squared	0.299	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	14.83		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *Price* (t) = -0.8671 (*p* = 0.38).

Table E3: Heterogeneity Analysis and Mechanism Validation, low-selling paddy producer households (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	-1.97	2.09	-0.94	0.34	-6.09	2.13	
2023	9.67	9.69	1.00	0.31	-9.32	28.67	
HH size	1.36	2.43	0.56	0.57	-3.40	6.13	
CDR	-0.09	0.15	-0.60	0.54	-0.38	0.20	
Head age	-0.41	0.36	-1.16	0.24	-1.12	0.29	
Head gender	1.65	7.77	0.21	0.83	-13.58	16.89	
Head educ. level							
Primary	13.47	9.05	1.49	0.13	-4.26	48.97	
Middle	-5.60	9.29	-0.60	0.54	-23.82	12.61	
Secondary	-5.44	7.69	-0.71	0.48	-20.52	9.64	
Asset wealth							
Medium	2.96	5.46	0.54	0.58	-7.74	13.66	
High	11.04	4.55	2.42	0.01	2.11	19.96	**
Land ownership	7.31	4.73	1.55	0.12	-1.95	16.59	
Production loss	-0.68	0.98	-0.70	0.48	-2.61	1.23	
Finance	4.10	3.93	1.04	0.29	-3.60	11.82	

Number obs	162	Kleibergen–Paap LM statistic	7.09
Number of clusters	48	Cragg–Donald Wald F	10.26
F-statistic	10.57	Kleibergen–Paap rk Wald F	13.95
Centred R-squared	0.549	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	12.78		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *Price* (t) = -0.9432 (*p* = 0.39).

The low-selling subgroup has a small sample size and relatively imprecise estimates; results for this group should therefore be interpreted cautiously.

Table E4: Heterogeneity Analysis and Mechanism Validation, high-selling paddy producer households (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	-3.53	1.72	-2.05	0.04	-6.92	-0.15	**
2023	-15.68	13.50	-1.16	0.24	-42.55	10.77	
HH size	-0.85	1.07	-0.80	0.42	-2.94	1.24	
CDR	-0.05	0.07	-0.70	0.48	-0.20	0.09	
Head age	-0.14	0.24	-0.59	0.55	-0.63	0.34	
Head gender	-9.64	7.89	-1.22	0.22	-25.12	5.82	
Head educ. level							
Primary	-9.46	8.82	-1.07	0.28	-26.76	7.83	
Middle	-11.30	6.61	-1.71	0.08	-24.28	1.66	*
Secondary	-8.47	4.66	-1.82	0.06	-17.62	0.67	*
Asset wealth							
Medium	-2.03	3.77	-0.54	0.59	-9.43	5.37	
High	0.05	4.50	0.01	0.99	-8.76	8.87	
Land ownership	-5.80	2.37	-2.45	0.01	-10.45	-1.15	
Production loss	1.45	1.34	1.08	0.28	-1.19	4.08	**
Finance	-1.14	3.37	-0.34	0.73	-7.73	5.54	

Number obs	468	Kleibergen–Paap LM statistic	11.5
Number of clusters	67	Cragg–Donald Wald F	45.305
F-statistic	7.62	Kleibergen–Paap rk Wald F	19.267
Centred R-squared	0.185	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	16.67		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *Price* (t) = -2.0478 (*p* = 0.06).

Table E5: Heterogeneity Analysis and Mechanism Validation, households in districts where APT 0 → 1 (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	-3.15	0.46	-6.78	0.00	-4.07	-2.24	***
2023[b]							
HH size	-3.11	3.22	-0.97	0.33	-9.42	3.19	
CDR	0.13	0.12	1.05	0.29	-0.11	0.39	
Head age	-0.18	0.32	-0.56	0.57	-0.81	0.45	
Head gender	-4.85	4.84	-0.95	0.34	-14.07	4.90	
Head educ. level							
Primary	-16.07	6.44	-2.49	0.01	-28.71	-3.43	**
Middle	-20.19	6.70	-3.01	0.00	-33.33	-7.05	**
Secondary	-17.16	3.72	-4.61	0.00	-24.46	-9.87	***
Asset wealth							
Medium	5.74	3.60	1.59	0.11	-1.31	12.80	
High	8.06	4.69	1.72	0.08	-1.13	17.25	*
Land ownership	5.99	3.85	1.67	0.09	-2.63	13.02	*
Production loss	1.50	1.10	1.36	0.17	-0.66	3.68	
Finance	-1.04	4.12	-0.25	0.80	-9.13	7.04	

Number obs	224	Kleibergen–Paap LM statistic	11.3
Number of clusters	13	Cragg–Donald Wald F	185.73
F-statistic	5900	Kleibergen–Paap rk Wald F	28.40
Centred R-squared	0.535	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	13.70		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *Price* (t) = -4.9393 (p = 0.00).

[b] Coefficient omitted due to collinearity.

Table E6: Heterogeneity Analysis and Mechanism Validation, households in districts where APT 1 → 0 (dependent variable: FCS).

Variables	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Price[a]	0.27	0.31	0.87	0.38	-0.34	0.89	
2023	13.35	1.73	7.68	0.00	9.99	16.76	***
HH size	1.33	0.96	1.39	0.16	-0.55	3.23	
CDR	0.01	0.05	0.23	0.81	-0.09	0.11	
Head age	-0.12	0.16	-0.76	0.45	-0.44	0.19	
Head gender	8.99	4.0	2.22	0.02	1.05	16.91	**
Head educ. level							
Primary	1.59	4.57	0.35	0.72	-7.37	10.55	
Middle	-1.86	4.83	-0.43	0.67	-10.46	6.72	
Secondary	-6.22	4.11	-1.51	0.13	-14.28	1.84	
Asset wealth							
Medium	-2.06	3.18	-0.65	0.51	-8.30	4.16	
High	0.08	3.07	0.03	0.97	-5.93	6.10	
Land ownership	1.55	1.99	0.78	0.43	-2.36	5.47	
Production loss	-0.35	0.78	-0.46	0.64	-1.89	1.17	
Finance	-0.47	2.05	-0.23	0.81	-4.50	3.55	

Number obs	838	Kleibergen–Paap LM statistic	15.20
Number of clusters	48	Cragg–Donald Wald F	268.34
F-statistic	20.83	Kleibergen–Paap rk Wald F	29.40
Centred R-squared	0.282	Stock–Yogo 10% maximal IV size critical value	16.38
Root MSE	14.20		

*** p<.01, ** p<.05, * p<.1

[a] Wild bootstrap-t, null imposed, 9999 replications, Wald test, clustering by FO, bootstrap clustering by FO, Webb weights: *Price* (t) = 0.8727 (*p* = 0.39).